THE USE OF ARTIFICIAL INTELLIGENCE TO PREDICT ROAD TRAFFIC NOISE

Barry Leonard Doolan

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Faculty of Science and Engineering

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This thesis is dedicated with much love to my wife, Judith.

Statements

This work contains no material which has been accepted for an award of any other degree or diploma in any University or other institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

Signed.....B. L. Doolan..... **Date**.....7th May 2008.....

Barry L. Doolan

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Abstract

This research has been motivated by the fact that present road traffic noise prediction models have not improved significantly since their development in the 1970s and 1980s, although road traffic noise nuisance is a significant and growing issue in Australia and elsewhere.

This thesis reviews the nature of road traffic noise, its measurement, and interpretation of noise levels in terms of noise nuisance. It then examines the principal noise propagation influences that are described by road traffic noise prediction models such as STAMSON and TNOISE, and outlines how these quasi-empirical models produce noise level predictions.

Present road traffic noise prediction models are essentially pattern recognition tools, but while they perform satisfactorily for very simple situations, accurate noise prediction in more complex situations is beyond their ability. However, artificial intelligence pattern recognition tools have proven their power and usefulness in a variety of applications in recent years, and this thesis examines the hypothesis that a neural network approach to predicting road traffic noise offers a way to move forward in noise impact assessment.

A simple two-layer feed-forward neural network architecture is found to be able to easily mimic present road traffic noise prediction models, with tangent-sigmoidal transfer functions specified for the input layer of 20-30 neurons, and a linear transfer function specified for the single output neuron. A priori rescaling of input values to roughly match the requirements of the transfer function facilitates the neural network training using a backpropagation algorithm with momentum and adaptive learning. Ways of avoiding the problem of overfitting are discussed.

A case study based on a 1993 noise impact assessment project is presented that demonstrates that a neural network can easily be trained from fairly limited field data to satisfactorily predict road traffic noise in site-specific situations, and the case study was one in which a model such as STAMSON or TNOISE is not able to perform well. The effort and expertise needed for this exercise is comparable to an air emission dispersion modelling exercise, a conclusion that should prove of great interest to road and environment authorities.

The thesis then proposes a strategy whereby grid-based neural networks can be developed to enable road traffic noise prediction in complex situations. The methodology is explained with the aid of a barrier adjustment calculation. The development of such a model for a site-specific situation is quite straightforward, but there is also clear potential to develop a generic 2-dimension modelling capability. The basic approach to this parallels the modelling strategy of present noise prediction models, but with reference sound levels and adjustments referred to a grid, and determined using neural networks.

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I am very grateful to my wife and family for their support, and many thanks also to the following people:

- My supervisors, Dr. Steve Carter and Dr. Greg Walker, partly for their technical assistance and partly for their forbearance in making a steep learning curve for me a lot smoother than I expected.

- Professor Frank Bullen, former Head of the University of Tasmania's School of Engineering for supporting my return to studies in my retirement years.

- Dr. Bill Wilson, Department of Primary Industries, Water and Environment, for his technical assistance and the loan of noise measuring instruments.

- Dr. Shao Ng for his assistance in helping me understand how to use Matlab.

- Mr. Jim Stephens, Environmental and Technical Services Consultant, for permission to use some of his data.

- Peter Doolan, my son, for his assistance in field work.

Supporting Work

This Masters research thesis is supported by on my extensive experience during a full time working career of 47 years in heavy industry and government. In the later part of my career I was employed as the Noise Specialist in the Tasmanian State Government for 16 years. In this capacity I carried out many investigations of noise problems throughout Tasmania, involving traffic, industrial and domestic noise issues. My work also included representing the State and Local Governments as an expert witness in noise at legal and planning hearings.

After retiring from my position with the State Government, I worked in private practice as a noise consultant, and at the same time I decided to undertake a Masters degree by research at the University of Tasmania's School of Engineering.

The research for this thesis was carried out from 2003 to 2007. Field work was undertaken at various locations around Tasmania. Other data in the thesis relevant to traffic noise were derived from work I carried out in private practice and during my employment by the State Government.

During the period 2003-2007, I carried out some 30-plus consulting assignments in noise, and was a member of a technical advisory panel that helped to prepare next generation noise legislation for Tasmania. A major document that I prepared during this time was:

Doolan, B.L. 2004. *Noise Measurement Procedures Manual.* Prepared under contract to the Tasmanian Department of Primary Industries, Water & Environment, July 2004.

Conference Paper

Doolan B.L., and Carter S.J., *The Use of Artificial Intelligence as a Tool to Assess Road Traffic Noise.* In Proceedings of the Annual Conference of the Australian Acoustical Society, Acoustics 2005, Busselton, Western Australia.

THE USE OF ARTIFICIAL INTELLIGENCE TO PREDICT ROAD TRAFFIC NOISE

Appendix

1.0 INTRODUCTION

1.1 Motivation

My name is Barry Doolan. I am a Member of the Australian Acoustical Society, a body of professionals employed in acoustics. I retired in 2001, having worked as an environmental professional for various Australian industrial and government institutions for nearly five decades, with the last 16 years of full time work as the Noise Specialist for the Tasmanian State Government. During this time, I undertook hundreds of investigations into road traffic noise complaints, and I have been an acoustics expert witness in many planning hearings and environmental appeals.

The Tasmanian road network is now substantially mature. The State and Commonwealth governments are responsible for some 3,500 km of roads, and local government is responsible for about 12,000 km of roads. Nevertheless, there is a steady stream of road upgrade projects and local residential development projects near to roads, and the way in which road traffic noise is assessed by the planning process is far from what might be hoped, especially given progress over the years in our ability to assess, for example, air emission dispersion.

The problem of road traffic noise nuisance is not unique to Tasmania. The Australian 2001 State of the Environment report estimated that 70% of the public is exposed to excessive road traffic noise levels (SoE, 2001). A key question that has led to this research is why does road traffic noise nuisance continue to be more of a problem than it should be? The answer, in my opinion, partly lies in the inadequate performance of present road traffic noise prediction models. These models are well known to be problematic for all but the simplest situations, such that regulatory authorities are unable to require road traffic noise modelling for complex situations, and often therefore noise nuisance is simply not properly assessed.

If a road traffic noise prediction modelling approach could be developed and be applied to sites with complex terrain, low and high traffic flows, variable time periods of day and night, and an assortment of road conditions with features such as buildings and barriers, then a major step forward in modelling noise would be made.

I discussed this problem with a fellow environmental professional, Dr Steve Carter, at the University of Tasmania. Dr Carter suggested that I explore the extent to which an approach based on artificial neural networks could mimic existing road traffic noise models, and then seek to extend this neural network modelling approach to more complex situations. He noted that existing noise prediction models are largely empirical in nature, that neural networks are powerful and elegant tools used to find patterns in data, and that they can easily handle multiple dimensional data.

1.2 Research Goals and Approach

Table 1.1 summarises the structure of this thesis, which reflects the research strategy developed to pursue the principal research goal, namely to examine whether a neural network approach to road traffic noise prediction could offer a way to overcome the deficiencies of present road traffic noise models regarding non-trivial applications.

Chapter 1	**Introduction**. Describes the research motivation goals and approach.
Chapter 2	**The nature of road traffic noise**. Reviews the nature of road traffic noise and noise nuisance, and its associated legislation
Chapter 3	**Present road traffic noise models.** Outlines out the physics of traffic noise propagation, describes the present traffic noise prediction models, exemplified by STAMSON and TNOISE, and discusses their application and limitations.
Chapter 4	**Neural networks for simple situation**. This chapter describes the nature of artificial neural networks, and explains why these pattern recognition tools are believed to offer a way to improve our ability to predict road traffic noise. The architecture of a neural network able to mimic STAMSON is defined, and illustrated by an example calculation.
Chapter 5	**Case study: the Hampshire mill project.** This 1993 project involved assessing noise impact of heavy vehicles in a situation similar to the kind of situation in which a classical noise prediction model is usually applied, but with proximity to the road and other factors precluding the use of such models. This chapter describes the successful application of a neural network model to the Hampshire data.
Chapter 6	**Modelling strategy for complex situations.** This chapter proposes a modelling strategy that uses grid-based neural networks to predict road traffic noise in 2-D situations involving complex terrain and road/barrier/building geometries. Such situations are quite beyond the ability of present models.
Chapter 7	**Conclusions and future work.** The chapter summarises the research presented in this thesis, and sets out recommendations for future research directions.

Table 1.1 Structure of this thesis.

2.0 THE NATURE OF ROAD TRAFFIC NOISE

2.1 The Nature and Measurement of Noise

Sound is generated when a vibrating source causes variations of air pressure that propagate through the air and are received by the human ear, an organ which is extremely sensitive to pressure changes. To gain an impression of the sensitivity of our hearing, atmospheric pressure is approximately 10^5 Pa, and the human ear is capable of detecting changes in air pressure of about 20 μPa within a frequency range of about 20 to 15,000 Hz.

Variations in air pressure are perceived by people as variations in sound (i.e. sound pressure levels), which are measured in decibels (dB). The decibel scale is logarithmic rather than linear to better describe the wide range of sound pressure levels to which the human ear can respond. Sound meters have electronics that weight (i.e. filter) the measured sound pressure level to reflect the response of the human ear to different sound frequencies. Sound pressure level measurements thus weighted are denoted as dBA or dB(A), rather than dB. The smallest change in sound pressure that a human ear can perceive is ~3 dBA.

The addition of logarithmic quantities is a little different from ordinary addition. For example, if a noise source produces a sound pressure level of 50 dB at a receiver and an identical noise source is placed alongside the first source, then the sound pressure level at the receiver increases by 3 dB to 53 dB. A 10 dB sound pressure level increment corresponds to a doubling of perceived loudness: for example, 60 dB is twice as loud as 50 dB and four times as loud as 40 dB.

The spectrum of sounds in the environment cannot be accurately described by a single quantity, and a number of parameters are commonly used to provide information on the spectrum. Noise standards are often set in terms of one or more of several such parameters. Definitions are provided by Australian Standard AS 1055.1-1997 *Acoustics - Description and measurement of environmental noise – general procedures,* and in brief:

- The equivalent sound pressure level (L_{eq}), is the constant sound pressure level that has the same energy as the time-varying sound pressure level measured over some period.

- The L_N sound pressure level is the sound pressure level equalled or exceeded for N% of the time. For example, L_{10} (18 h), sometimes denoted $L_{10\ (18\ h)}$, is the sound pressure level equalled or exceeded for 10 % of an 18 hour period.

- The maximum and minimum sound pressure levels (L_{max} and L_{min}) are the maximum and minimum root-mean-square sound pressure levels measured over some period.

Sound pressure levels are measured in Australia and New Zealand in accordance with Standards prepared by the A/NZ Joint Standards Committee AV/5 on Acoustics. The two standards of relevance to road traffic noise assessment are *AS 1055: Acoustics - Description and measurement of environmental noise*, and *AS 2702: Acoustics - Methods for the measurement of road traffic noise*. A supporting standard to assist in assessing noise levels within buildings is *AS 2107: Acoustics - Recommended design sound levels and reverberation times for building interiors.*

Traffic noise measurements are usually made using a statistical sound pressure meter, as shown in Figure 2.1, following the procedures detailed in whichever of the above Australian standards is applicable to the measurement required.

Figure 2.1 The author using a sound pressure meter to measure traffic noise.

Ancillary measurement information, such as the specific noise descriptor to be measured, or the measurement duration, is set out in noise measurement procedure manuals prescribed by each State. The author developed the manual currently used in Tasmania (Doolan, 2004) under a consulting contract with the State Government.

Road traffic noise descriptors used in legislation vary across Australia. The L_{10} (18 hour), L_{eq} (24 hour), and other descriptors are all used, and there is no standard approach. Specific state legislation includes Queensland EPA (2000); Victoria EPA (2003); WA DEC (1986); and DPIWE (2004).

2.2 Sources of Traffic Noise

Road traffic noise can be separated into bulk traffic noise and intermittent traffic noise (Victoria EPA, 2002). In general, the traffic composition and volume, the gradient of the road, the traffic speed, and the number of lanes of traffic all contribute to the variability in noise levels from traffic. The noise itself is mainly generated by a vehicle's engine, exhaust system, tyre-road interaction, brakes, and aerodynamic effects, as shown in Figure 2.2.

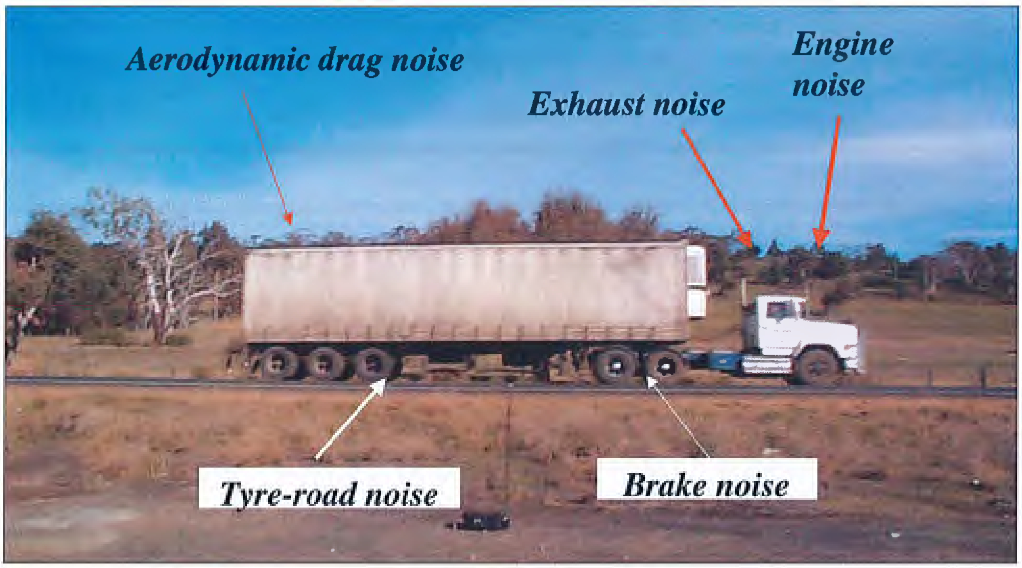


Figure 2.2 Principal sources of noise from a vehicle.

Bulk traffic noise is the component of the total road traffic noise which is roughly constant in nature, resulting from the overall effects of noise emissions from traffic travelling along a road. At low traffic speeds, the majority of road traffic noise is generated by vehicle engines, transmissions, exhausts and brakes. As the speed of the traffic increases, noise from the interaction between tyres and the road increases and, at speeds over about 70 km/h, this becomes the dominant component of the bulk traffic noise. Air disturbance by moving vehicles also becomes an important factor at higher speeds.

Intermittent traffic noise is caused by individual vehicles and generally manifests itself as an intrusive noise of a usually short-term nature, superimposed on the background bulk traffic noise.

Sources of intermittent traffic noise include:

- heavy vehicles, which are inherently louder than medium or light vehicles;
- modified cars and motorcycles;
- truck air brakes;
- exhaust systems; and
- vehicle horns.

Stop-start braking and acceleration of vehicles departing from traffic lights are also well known sources of intermittent noise. On hills, the noise of engine braking and high-revving of engines in low gear also stand out from the steady bulk traffic noise. Heavy vehicles contribute more significantly than medium and light vehicles to the overall traffic noise level. In the case of heavy vehicles which are not fully laden, significant noise levels can be generated by vibration, and rattling.

2.3 Road Traffic Noise Legislation

Road traffic noise legislation is expected to prescribe:

1. Acoustic objectives (i.e. noise levels) which can be used to guide assessment of noise impact and development planning.
2. Methodologies by which noise levels are determined (i.e. measured or predicted).
3. Procedures by which noise impact is assessed in land use planning.
4. Actions that regulatory authorities should take when noise levels exceed the prescribed acoustic objectives.

Acoustic objectives.
There has been a steady convergence of agreement in environmental legislation by nations around the world over the past decade or so, but unfortunately this convergence is less complete for noise legislation than in other areas, such as air quality. Table 2.1 shows typical acoustic objectives set by jurisdictions across Australia and overseas.

Day time	L_{eq}	L_{max}
0700 to 1800 h Monday to Saturday	50	67
0900 to 1800 h Sundays and holidays	45	62
Evening 1800 to 2200 h All days	45	62
Night time		
2200 to 0700 h Monday to Saturday	40	57
2200 to 0900 h Sundays and holidays		

Table 2.1 Typical acoustic objectives (dBA) for residential usages.

Table 2.1 is representative of international best practice, with the caveat that some jurisdictions use alternative road traffic noise descriptors and/or alternative definitions of day time verses evening or night time. In particular, road traffic noise levels impacting residential usages in Australia are often set in terms of L_{10} (18 h), with 63 dBA being the limit usually prescribed. This lack of consistency has demonstrated potential to cause some confusion, and the problem has not yet been resolved.

Development of standards for transport vehicle noise emissions in Australia is carried out in a collaborative fashion between Commonwealth and State regulatory authorities, and industry groups. The results are embodied in the Australian Design Rules, and the ADR 83/00 standard for vehicle noise emission levels is considered to be in line with best practice expectations. This standard is being implemented over the 2005-2007 period.

Noise Level Determination
The procedures for making noise measurements using sound pressure level meters are fairly well agreed, as discussed in Section 2.1. A second aspect of noise level determination is the prediction of noise levels for proposed road, traffic and residential developments. Examples are noise levels from a new road, noise levels due to expected traffic growth or an expected change in traffic composition, and noise levels impacting the upper level bedroom of a dwelling yet to be constructed.

Another principal motivation for road traffic noise predictions to be based on computer modelling is that the predictions can be made on a statistical basis using Annual Average Daily Traffic counts and mean traffic composition breakdown. This is considered to be more reliable than short-duration noise level measurements which are subject to the uncertainty of natural fluctuations in traffic volume and composition.

Noise impact assessment procedures
The consideration of noise impact as a routine part of development applications is standard practice in many countries. In Canada, noise impact assessments are usually required to be supported by computer model noise predictions, although such predictions are well known to be problematic for all but the simplest situations. It is partly the problematic nature of road traffic noise prediction by computer models that has resulted in Australian regulatory authorities not requiring their use, or at least not placing significant reliance on the predictions.

In particular, applications for residential development planning approvals are not routinely required to be supported by noise impact studies, even when the development location has clear potential to be exposed to excessive noise levels. Nor is account usually taken of the fact that future road traffic noise levels will be higher than present noise levels if traffic volumes increase, especially since such increases have been recorded everywhere in Australia, and the nation's road traffic is continuing to grow.

Noise mitigation procedures
One of the motivations for this research was the observation that road traffic noise nuisance is a considerable problem across Australia. Controlling noise emissions from individual vehicles is already done fairly well, and cannot solve the fundamental problem of noise emissions from significant traffic volumes impacting nearby noise sensitive usages.

The issue of noise nuisance mitigation can be separated into those problems which already exist; and those which are foreseen prior to approval of road construction / upgrade work, or prior to approval of a noise sensitive development. Mitigation measures to alleviate situations of manifestly excessive noise levels include the provision of acoustic barriers, but there are so many such situations and such remedies are so expensive, that the emphasis to date has been to address problems on a priority basis, subject to budget availability.

Australia often fails to measure up to international best practice by not requiring noise impact studies to support development applications, as noted in the previous section. There is no national approach to road traffic noise management in Australia, with each jurisdiction prescribing its own approach to mitigating the effects of excessive traffic noise. Considering Tasmania, noise legislation has, with only minor exceptions, not been updated since promulgation of the *Environment Protection (Noise) Regulations* (1977). Noise levels are thus assessed against best practice standards established by other jurisdictions, the authority for this being Section four of the *Environmental Management and Pollution Control Act (1994).* In the case of road traffic noise, the Tasmanian State Government considers best practice legislation to be represented by the New South Wales publication *Environmental Criteria for Road Traffic Noise* (NSW EPA, 1999).

The Canadian Province of Ontario provides an example of best practice overseas. Ontario has developed successive generations of noise legislation, and the procedures set out in MOE (1997) are far more advanced than current procedures in Tasmania. In Ontario, the environmental groups of most consulting engineering firms include acoustics expertise, while in Tasmania such expertise is almost non-existent. In Ontario, if the required noise impact study predicted a problem with excessive noise levels, then a number of remedies are available. The primary goal is to provide mitigation measures that result in compliance with the noise level standards and, to this end, an acoustician is expected to work with the architect to incorporate acoustic mitigation measures into the building design. In some case, the development title must include an appropriate warning clause if there is a risk of residual noise nuisance, but such measures are virtually unheard of in Australia.

2.4 Noise Nuisance

There has been much literature published over the years to describe the perception of noise (e.g. Harris, 1979; Magreb, 1975). Whilst noise is an inescapable part of life, it is common experience that noise affects different people in different ways. Noise can be defined as unwanted sound, and there is an expectation by the public that regulatory authorities should take steps to be protect people from noise nuisance. Noise nuisance impacts can be broadly separated into those which causes mere disturbance, and more severe impacts associated with adverse health effects such as hearing loss, sleep deprivation, and persistent anger.

Figure 2.3 shows the author's interpretation of the main interactions between noise and the behaviour of the community. Considering the upper portion of Figure 2.3, during the day interruptions to quality of life activities account for the majority of complaints from residents, schools and others about noise nuisance. At night, it is common knowledge that noise nuisance causes disruption of sleep patterns, and intermittent traffic noise is often most noticeable at night. There is now a large body of literature that examines the links between noise nuisance and health, for example Davis & Stevens (1983); Job (1996); WHO (1999); and SoE (2001).

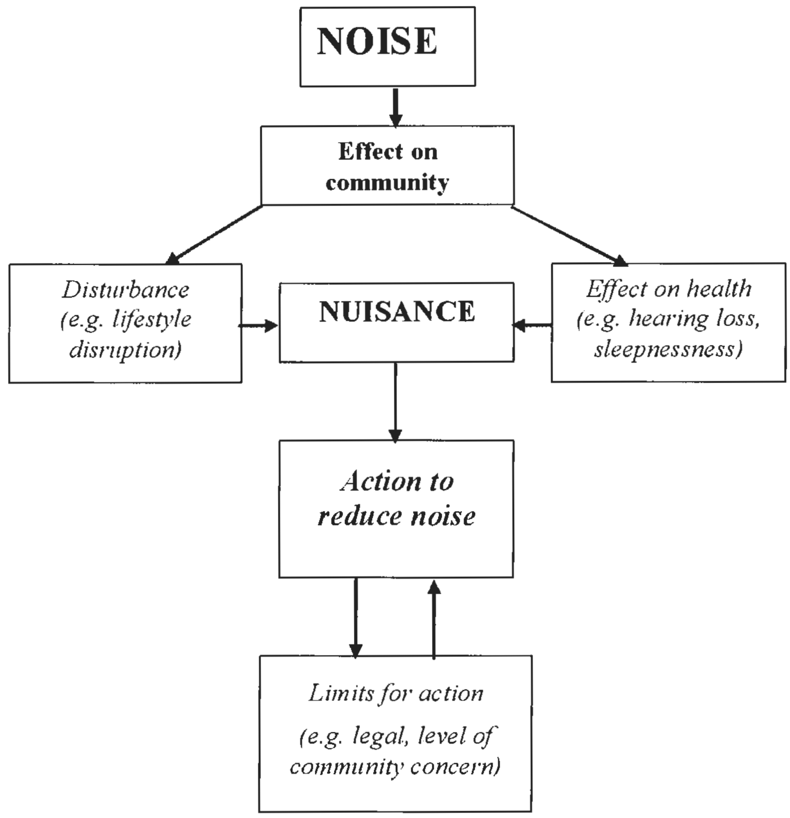


Figure 2.3 The general effects of noise nuisance.

Considering the lower portion of Figure 2.3, the community reaction to noise nuisance, which depends on the response of individuals (e.g. light vs heavy sleepers) and the nature of the community (quiet suburb vs central city area), is usually to demand that action be taken to reduce the noise. The community has an expectation that complaints to the relevant authority responsible for administering any noise regulations should result in the resolution of noise issues. However, the authority also has a responsibility to ensure that it acts within its legal framework, which often results in problems when dealing with, for example, nuisance from a barking dog.

Table 2.2 shows the expected public reaction when a noise level (i.e. a sound pressure level) exceeds a standard in a residential area, taken from AS 1055-1973 *Noise Assessment in Residential Areas*. This standard is a little outdated, but remains generally correct.

Exceedance (dBA)	**Nuisance**	**Public reaction**
0 – 5	Marginal	From no observed reaction to sporadic complaints
5 – 10	Little	From sporadic complaints to widespread complaints
10 – 15	Medium	From widespread complaints to threats of community action
15 – 20	Strong	From widespread complaints to threats of community action
20 – 25	Very strong	From threats of community action to vigorous community action
25 and over	Extreme	Immediate direct community and personal action

Table 2.2 Link between exceedance of a noise standard and public reaction (AS 1055).

The degree of noise nuisance associated with a measured noise level requires modification in some circumstances, notably if the noise contains intrusive characteristics such as tonality, impulsiveness, modulation, or a low frequency component. A total adjustment of up to 10 dB can be made to the measured sound levels in the case of multiple intrusive noise characteristics. In the case of road traffic noise, one intrusive characteristic that has attracted much attention in recent years is the use of air brakes by heavy vehicles, prompting signage warning heavy vehicle drivers to avoid using air brakes in residential areas.

Noise nuisance is a complex subject, and in the case of road traffic noise a rule-of-thumb used by many acousticians that parallels Table 2.2 is that a noise level 1-5 dBA above an acoustic objective can be described as constituting slight noise nuisance, while noise levels 5-10 dBA above the objective are described as constituting definite or significant nuisance. If the noise level is more than 10 dBA above the standard, then the nuisance is described as severe, and mitigation action is often mandatory, such as installation of noise barriers or a reduction in posted speed limits.

For example, if the L_{eq} (day) = 50 dBA standard is used by a regulatory authority, than a noise level of L_{eq} (day) $\geq$ 65 dBA would indicate the need for mitigation. Alternatively, if the L_{10} (18 h) = 63 dBA standard is used, then a noise level of L_{10} (18 h) $\geq$ 73 dBA would indicate the need for mitigation.

In quiet rural areas, noise levels are typically about 32 to 35 dBA at night whilst quiet urban night-time noise levels typically lie between 40 to 50 dBA. In the author's experience, day time noise levels in noisy urban areas frequently lie between 70 to 80 dBA, with road traffic generating much of the noise. To put this in perspective, normal conversation becomes difficult when ambient noise levels are in the range 60 to 65 dBA.

Cars and trucks are a major cause of noise in many urban areas with SoE (2001) estimating that 70% of environmental noise in urban areas is due to road traffic. More generally, the National Transport Commission reports that studies of the Australian population show that nearly 40% is exposed to undesirable road traffic noise with a further 10% exposed to excessive road traffic noise (NTC, 2001).

2.5 The Janus Perspective

It is instructive to examine the evolution of the road traffic noise nuisance issue, based on my experience as an acoustics practitioner. Considering first the historic situation, Table 2.3 shows a sample of typical noise measurements that the author recorded up to about ten years ago in response to complaints of road traffic noise nuisance from residents living in dwelling near roads in Tasmania. The reported values were each calculated as the mean of a series of eighteen L_{10} (1 h) dBA measurements, in accordance with *AS 2702: Acoustics- Methods for the measurement of road traffic noise.*

Date	Site	L_{10} (18 h) dBA
August 1986	Conara Road, Montague Bay	64.0
July 1991	Sirius St., South Arm Highway	67.4
August 1991	Dover Court, South Arm Highway	69.6
August 1991	Dover Court, South Arm Highway	68.2
September 1991	Sirius St., South Arm Highway	66.4
September 1994	Montague St., New Norfolk	61.7
November 1994	Cradoc to Cygnet	62.3
January 1995	Bass Highway, Somerset	71.4
January 1996	Esplanade, Burnie	62.5
January 1996	Mersey Main Road, Spreyton	67.0
March 1997	Trevor St., Ulverstone	66.3
October 1998	Gilbert St., Latrobe	69.8

Table 2.3 Road traffic noise levels at various residential sites in Tasmania. See text for discussion.

Table 2.3 shows that noise nuisance from road traffic noise dates back at least two decades in Tasmania, even though the state is largely rural in nature. All the road traffic noise levels in Table 2.3 are comparable to, or exceed, the commonly used L_{10} (18 h) = 63 dBA standard.

Figure 2.4 shows more recent noise level measurements I made using an acoustic logger in a residential area near a main road as part of a consulting assignment for the Port of Devonport authority. The noise measurements consist of a L_{eq} (15 min) dBA values, and have been processed using the Matlab technical computing package.

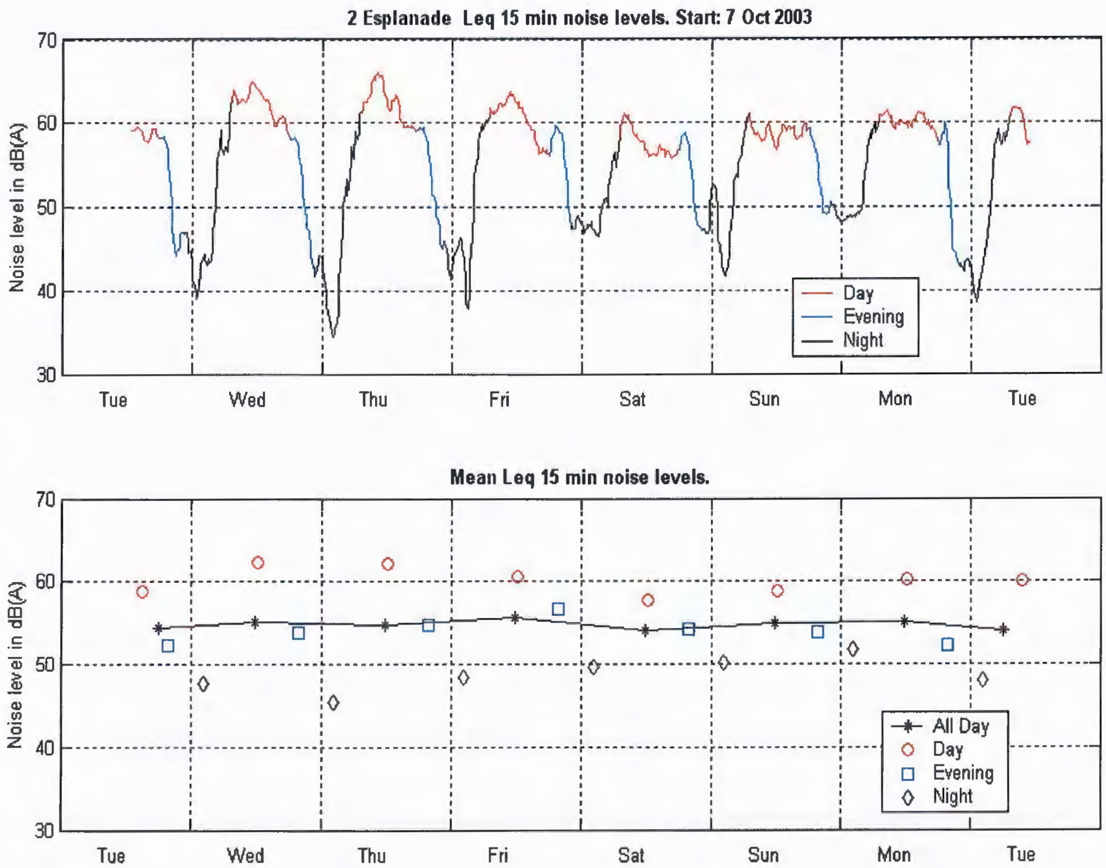


Figure 2.4. Diurnal traffic noise in a residential area of Devonport, Tasmania.

The measurements shown in Figure 2.4 are colour-coded to reflect the period to which they relate: day time (07:00h to 18:00h), evening (18:00h to 22:00h) and night time (22:00h to 07:00h). The mean L_{eq} values for these periods are displayed in the lower panel of the figure, and can be compared to the typical acoustic objectives set out in Table 2.1. It is clear that the noise levels are generally 10 dBA or more above the acoustic objectives for all three periods, indicating distinct to severe noise nuisance.

Excessive noise levels, such as those recorded in Figure 2.4, are often encountered by acousticians in Australia. There has been a steady rise in the extent and severity of road traffic noise nuisance over the past few decades, and the growing vehicle fleet provides additional evidence of this.

Figure 2.5 shows a steady growth in vehicle sales since the mid-1990s, and in 2006 about 81,000 new vehicles per month were sold in Australia (ABS, 2006). However, in this case the past is not necessarily a good guide to the future. The Australian vehicle fleet has now largely matured with ownership of light vehicles saturating at about 520 cars per 1,000 people (SoE, 2001). The commercial fleet is expected to continue to rise slightly, but the overall finding is that future growth in the size of the Australian vehicle fleet is essentially tied to the nation's population growth, especially with the rising costs of running a vehicle.

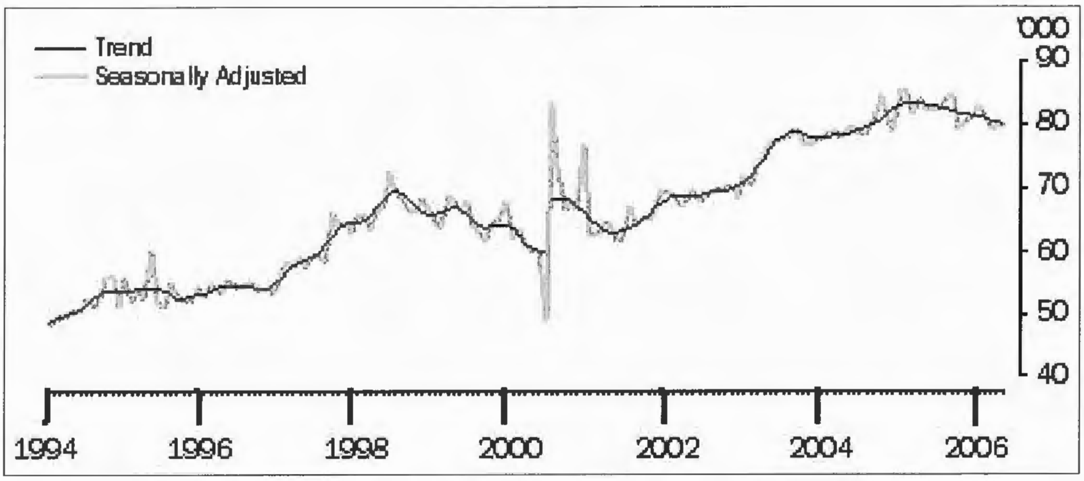


Figure 2.5 Australian all vehicle sales, 1994-2006 (ABS, 2006).

Of course, some cities in the world have very severe traffic problems compared to Australia's capital cities, and yet are nevertheless experiencing run-away ongoing growth in these problems. Cities such as Bangkok (see Figure 2.6) have large populations, but inadequate transport infrastructure, and are not yet at vehicle ownership saturation.

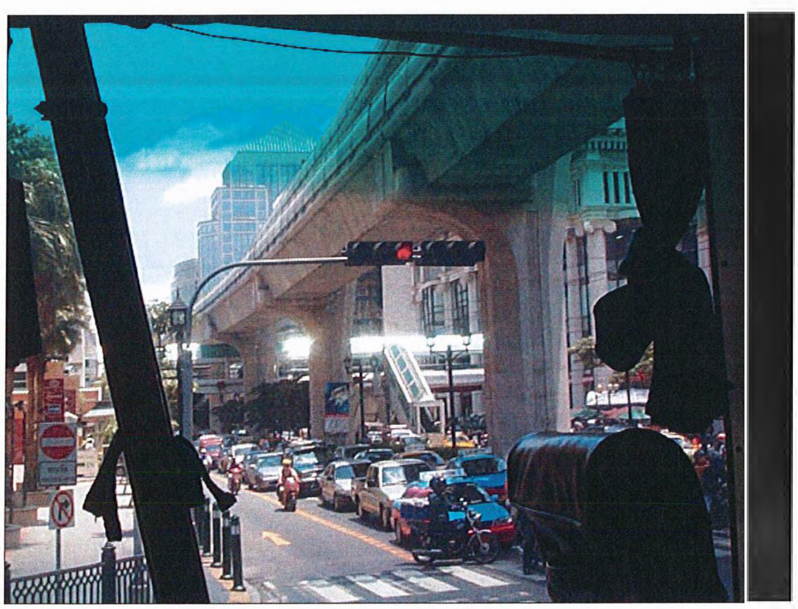


Figure 2.6 Rush hour in Bangkok, Thailand

In the lead-up to the 2008 Olympics, the incredible traffic problems of Beijing have been highlighted by numerous news stories, and yet some 10,000 new vehicles per day are registered in this one megacity. The need for transport authorities and other decision makes to have good road traffic noise prediction models is clear. Unfortunately, as discussed in Chapter 3, there has been little progress over the past two decades towards improving the models that were developed in the 1970s and 1980s, which are only capable of handling relatively simple situations.

3.0 PRESENT ROAD TRAFFIC NOISE MODELS

3.1 Road Traffic Noise Physics

The physics of sound propagation through the atmosphere in practical road traffic noise prediction situations is non-trivial, although the basic mechanisms are well understood. In general, the propagation of sound away from a noise source is principally subject to:

- geometric spreading and ground attenuation;
- elevation and barrier effects; and
- atmospheric absorption and refraction.

Common road traffic sound level prediction models consider these effects in a largely empirical fashion, although the Environmental Noise Model discussed later in this chapter places more reliance on theoretical descriptions of sound propagation effects.

Geometric spreading and ground attenuation

Geometric spreading of sound waves from a point source reduces sound flux according to the usual inverse square law, producing a 6 dB attenuation for a doubling of distance from the source. In the case of a road approximated as an infinite straight line, the geometric spreading is a cylindrical expansion, which produces an attenuation of 3 dB for every doubling of distance from the source (Sutherland, 2000).

Absorption of sound energy by the ground has an important influence on the attenuation of noise. Sound propagates with least attenuation over water and hard surfaces, and for the purpose of predicting noise levels from road traffic over distances from the road of ~100 m or less such surfaces are assumed to be acoustically reflective, with no sound absorption.

Soft ground, such as grassy terrain, attenuates sound more than harder, more reflective ground. Noise prediction models take the geometric spreading of sound waves, and the attenuation of sound by the ground, into account by applying an semi-empirical *distance adjustment* to sound level predictions which typically has the form:

$$10\,(1+\alpha)\,\log_{10}\,(D_{ref}/D) \qquad \text{Eqn 3.1}$$

Where D is the distance from the noise source to the location of interest, D_{ref} is the reference distance at which the sound pressure level has been measured, and the parameter α is zero for reflective surfaces and 0.66 for very absorptive ground.

Box 3.1 provides an example of this calculation from a consulting project carried out by the author in 2007, near Burnie in northern Tasmania. The noise source was an excavator, but the calculation would be the same for road traffic noise.

Box 3.1 Example of the distance adjustment.

In a 2007 project in Tasmania, the author measured a noise level of L_{eq} (1 min) = 73.9 dBA at $D_{ref} \approx 3.5$ m from an excavator working in waste disposal site, using a Bruel & Kjaer (B&K) 2230 Precision Integrating Sound Level Meter. Calibration checks were made before and after the tests using a B&K 4230 Sound Level Calibrator. No calibration drift was noted. The weather was good, with little wind and an air temperature of about 15°C.

Noise levels of L_{eq} (1 min) = 46.3 dBA and 45.4 dBA were recorded immediate after the on-site measurements at a location near the waste disposal site, with a line-of-sight view of the excavator some $D \approx 200$ m away. The two sets of noise measurements are consistent for a value of $\alpha \approx 0.5$, quite appropriate for the intermediate terrain.

Elevation changes and barriers

Figure 3.1 shows the geometry of a typical situation involving both ground elevation change and a barrier between the road and a receiver. Direction (a) → (b) follows the direct line-of-sight taken by the noise from the vehicle, and separates the illuminated (or "bright") zone from the shadow zone. Some noise is reflected from the barrier, as shown by direction (c), whilst the noise experienced by the receiver shown in the figure is that component of the sound which is diffracted over the barrier into the shadow zone, in direction (d).

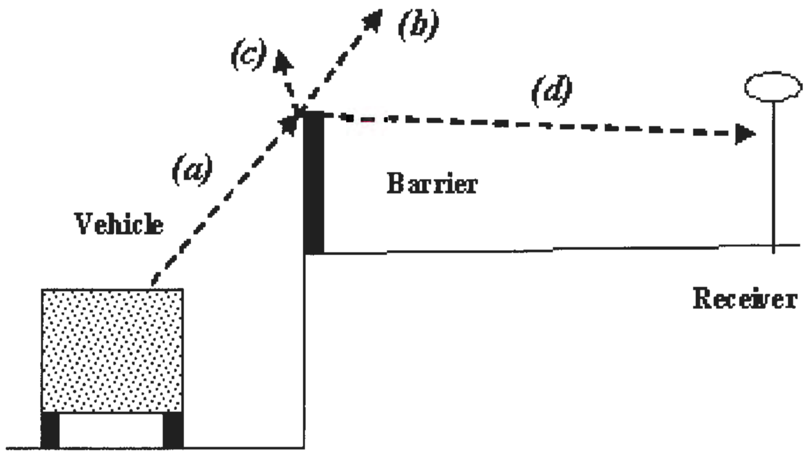


Figure 3.1 Typical situation involving a ground elevation change and a barrier.

Road traffic noise prediction models take these effects into account in one of two ways. Some models, such as TNOISE, apply empirical *elevation change* adjustments and empirical *barrier adjustments* to the free field sound level predictions (UK DoT, 1988). These are essentially look-up tables that are hard-coded into the computer model. Other models, such as STAMSON, apply basic diffraction theory to compute the barrier adjustment using Fresnel-Kirchhoff integrals (e.g. Schroter & Chiu, 1989; Marion & Heald, 1980). In the author's experience, the two methods produce similar results for simple barrier geometries.

Atmospheric absorption and refraction

The physics of *atmospheric absorption* of sound is discussed by Piercy et al. (1977), Bass et al. (1994), and Larsson (2000). In brief, atmospheric absorption of sound depends on the relative humidity, temperature and density of the atmosphere, and it also depends on the sound frequency (i.e. absorption is a dispersive phenomenon). Standards for calculating the amount of sound absorption in a given situation include the American National Standard ANSI S1.26-1995 (R2004) *Method for the Calculation of the Absorption of Sound by the Atmosphere*, and the ISO standard ISO 9613-1:1993 *Acoustics - Attenuation of sound during propagation outdoors - Part 1: Calculation of the absorption of sound by the atmosphere.*

The propagation of sound is affected by other processes that are only significant over longer distances than are usually of interest to road traffic noise models, and which thus are not considered by the standard workhorse road traffic prediction models. One effect is atmospheric absorption, which is greater than spreading losses over long propagation distances, especially for higher frequency sound (Sutherland, 2000). However, it does not significantly attenuate sound levels over the distances of 100 m or less that are typically considered by road traffic noise prediction models, and can be ignored for the purpose of the present research.

Another such effect is the *refraction* of sound waves, which occurs if the sound velocity and/or wind speed changes along adjacent ray paths. Sound rays are bent downwards in downwind conditions and upwards in upwind conditions. There is assumed to be little effect of downwind conditions on sound levels, but upwind conditions create shadow zones which can result in attenuation of sound of up to 25 dB.

The speed of sound, *c*, in air depends on absolute temperature, *T*, as follows:

$$c = \sqrt{1.4\,RT} \qquad \text{Eqn 3.2}$$

where the gas constant is R = 287.03 J kg^{-1} K^{-1}. At distances from a road greater than about 100 m, sound wave refraction occurs due to vertical temperature changes in the atmosphere. In particular, if the air temperature increases with height under inversion conditions, then refraction bends sound waves downwards, resulting in increased noise levels at ground level (Holmes Air Sciences, 1997). This can create shadow zones, such that only a segment of road contributes to the noise observed by the receiver at some location (Makarewicz, 1997).

3.2 Typical Road Traffic Noise Models

Many road traffic noise prediction models have been developed over the years, all of which are quite similar. The platform research underpinning these models was largely carried out in the late 1960s and early 1970s, when road traffic noise first became a significant issue that was sufficiently wide spread in nature to prompt such research work. In the United States, an early road traffic noise model was developed by the Federal Highway Administration (Barry & Reagan, 1978), while Britain developed the *Calculation of Road Traffic Noise* procedure (UK DoT, 1988), which is usually referred to as "The Welsh Method", since the publication was issued by the Welsh office of the U.K. Department of Transport.

Two computer models that were developed from these early methodologies, and which are frequently used to assess compliance with regulations by many Australian transport and environmental authorities are TNOISE and STAMSON. A third model, the Environmental Noise Model (Tonin, 1986), illustrates a more theory-dependent approach, and together these three models illustrate the state-of-the-art and the motivation for the present research.

TNOISE and STAMSON are road traffic noise prediction models that are so similar they can be discussed together. TNOISE was developed by the Department of Main Roads, Western Australia from a 1988 updated version of the Welsh Method (UK DoT, 1988), while STAMSON was developed by the Ontario Ministries for the Environment and Transportation, and is largely based on the U.S. Federal Highway Administration's Highway Traffic Noise Prediction Model, mentioned above, and often termed the "108 model".

The "108 model" was replaced in 1998 by the FHWA Traffic Noise Model (TNM), which was based on a new database of 1990s vehicle noise emission measurements (Menge et al., 1998). The TNM is a distinctly better model and includes more recent acoustical algorithms, with particular advances in barrier acoustics, but it essentially has the same approach to sound level prediction as the earlier "108 model" and STAMSON.

The methodology of STAMSON is set out in the *Ontario Road Noise Analysis Method for Environment and Transportation* (Schroter & Chiu, 1989). STAMSON computes equivalent sound levels, L_{eq}, over any time period, while TNOISE computes L_{10} (18 h) and L_{10} (1 h) sound levels, and can convert L_{10} noise levels to L_{eq} values. As discussed in Chapter 2, both L_{eq} and L_{10} sound spectrum descriptors are commonly used by regulatory authorities.

TNOISE and STAMSON consider the sound propagation effects outlined in the previous section in a largely empirical fashion. Road traffic engine and tyre-road noise emissions are aggregated into a reference noise level at a specified distance from the road, and this reference noise level is treated as the de facto noise source. The various noise propagation effects are parameterised on the basis of empirical data, and the overall correction to the reference sound level is computed using a logarithmic summation.

Considering STAMSON, to illustrate the general approach used by both models, a reference equivalent sound level, L_o, is computed for each of three classes of vehicles (light, medium and heavy) at a reference distance of 15 m from the road side, for a reference traffic volume of 40 vehicles per hour, equally spaced, and travelling at the posted speed limit, S (km/h). The reference equivalent sound level for heavy vehicles is:

$$(L_o)_{HV} = 24.6 \log S + 38.5 \text{ dB} \qquad \text{Eqn 3.3}$$

An overall reference equivalent sound level is computed by logarithmically adding the three component reference equivalent sound levels, weighted by the actual percentage of vehicles in each of the three classes, P_i, and adjusted by a road gradient factor, K_g.

$$L_{ref}(\text{dB}) = 10 \log \sum_{i=1}^{3} \{K_g \, P_i \, 10^{(L_o)i/10}\} + 10 \log V_{ref} - 10 \log S + 10 \log D_{ref} - 25 \qquad \text{Eqn 3.4}$$

The overall reference equivalent sound level is then adjusted for actual distance, actual traffic volume, barrier effects, pavement surface type, and the presence of any intervening woods or rows of houses (Schroter & Chio, 1989; UK DoT, 1988). The reference equivalent sound level is also adjusted if a finite segment of road is being considered, wherein lies a key to the usefulness of these models: they can address situations involving roads that are not completely in the line of sight of a receiver, typically because part of the road is hidden by buildings and/or barriers; and they can also address multiple roads or roads with several lanes of traffic. They do this by breaking the roads into sections, and computing the overall noise level prediction as the sum of the component sections.

STAMSON's Graphical User Interface window is shown in Figure 3.2, showing the model being applied to a situation involving an elevation change and a barrier.

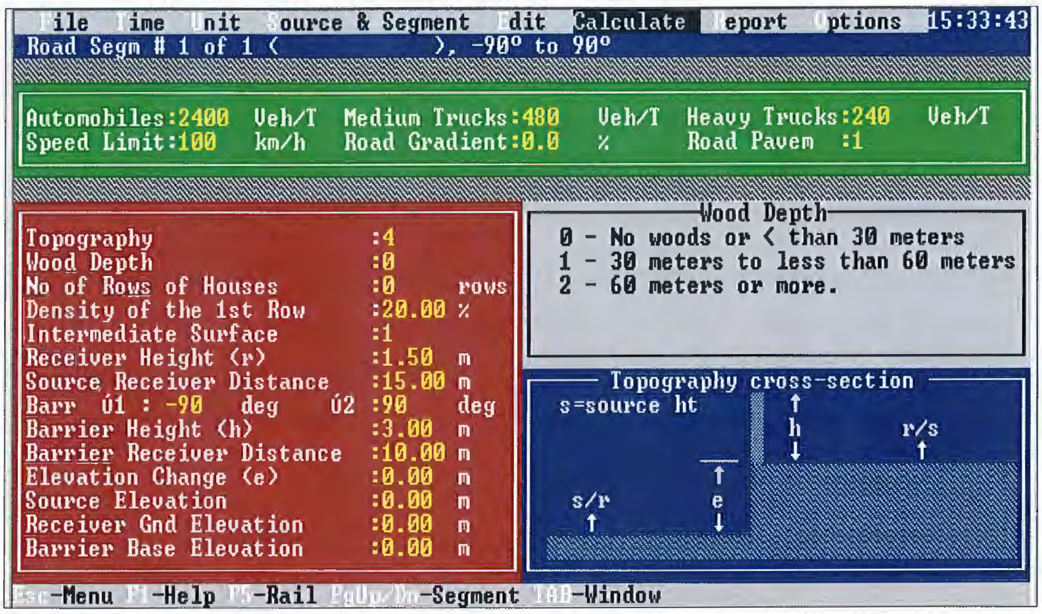


Figure 3.2. The STAMSON Graphical User Interface

The Environmental Noise Model (ENM)

ENM was developed by the Australian company RTA Technology Pty Ltd, and is a model of wide applicability which uses a mix of empirical data and theory. The ENM calculation is (Tonin, 1986):

$$L_p = \sum_{\text{All sources}}^{Log} \left[L_{source} + D - \sum_{i=1}^{5} A_i \right] \qquad \text{Eqn 3.5}$$

Where L_{source} is the reference sound power level of the source (dB re 10^{-12} W), D is a frequency independent source directivity correction, and the five A_i terms are corrections to the reference sound power level for geometric spreading, ground attenuation, barrier attenuation, air absorption, and wind & temperature effects. The outer summation over the sources is a logarithmic summation.

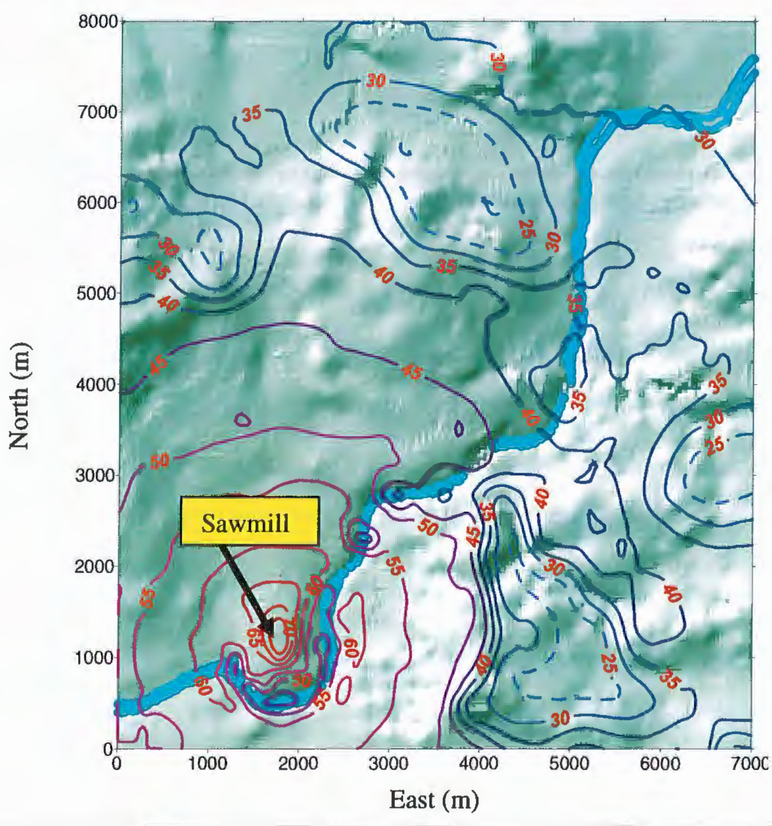
ENM's calculation methodology is similar to the specialist road traffic noise prediction models TNOISE and STAMSON, although its algorithms are largely based on those set out in CONCAWE report 4/81 (Manning, 1981) whereas TNOISE and STAMSON evolved from earlier more empirical modelling procedures.

ENM can model point, line, plane or surface noise sources, together with air absorption, wind and temperature effects. These additional modelling capabilities are only significant over distances greater than those generally considered in most road traffic noise prediction situations, and for road traffic noise modelling a disadvantage of ENM is the need to input sound data in either one-third or octave sound power levels, which are not widely used as road traffic sound spectrum descriptors. However, an advantage of ENM is that it can model the effects of variable terrain by applying Maekawa barrier attenuation theory to terrain that blocks line-of-sight to a noise source (Maekawa, 1968; Fujiwara et al., 1973; 1977a; 1977b).

Australian regulatory authorities are familiar with using ENM to examine the impact of existing or proposed industrial or other point noise sources, but the model is not widely used for road traffic noise prediction. Box 3.2 provides an example of the use of ENM to assess noise impact from a proposed industrial development project in 2001.

Box 3.2 Example of the use of ENM for point noise source modelling.

In a 2001 project in southern Tasmania, the author while working as an acoustics specialist with the State Government, used ENM to predict the impact of noise emissions from a sawmill and associated operations. The terrain was reasonably complex, and although there were few residences in the immediate vicinity of the sawmill, there was some concern that topographic noise channelling might result in noise nuisance further from the industry. The below figure, prepared by the author, shows ENM predicted noise contours (dB) on a map.



3.3 Model Applications and Limitations

Comparison to Air Dispersion Models

An interesting comparison can be made between air emission dispersion models and road traffic noise prediction models. Both fields of environmental practice were developed in the 1970s and 1980s to similar degrees of sophistication. At that time, existing simple air dispersion models could not be applied to situations involving complex terrain, since a simple spreading-disc model prediction based on a single wind speed and direction is only able to crudely model factors such as building wake effects or the impingement of a plume on a hill. The failure to handle non-trivial situations was also true of existing road traffic noise prediction models, which could not handle situations involving complex road geometries, complex layouts of near-road buildings or barriers, or complex near-road terrain, perhaps involving a mix of ground types.

The workhorse Australian air dispersion model, *Ausplume,* was developed in the 1980s (Lorimer, 1986), based on the United States Industrial Source Complex models (Bowers et al., 1979). At the same time, road traffic noise prediction models such as STAMSON and TNOISE were developed, and both fields of environmental practice were justifiably pleased at having taken large steps forward.

The use of computer dispersion models, instead of hand calculations, enables predictions to be made on a statistical basis, by examining air quality predictions associated with a year or more of meteorology. The same is true of the 1980s generation of road traffic noise prediction models, which are driven by Annual Average Daily Traffic (AADT) data, and traffic composition statistics based on long term observations. This represented a significant advance in environmental regulation, since air quality standards could be specified in terms of ambient ground level concentration limits instead of in-stack contaminant concentrations, while road traffic noise could be assessed without relying too heavily on short term field measurements which might not be very representative of the long term traffic noise.

In the 1990s more sophisticated diagnostic and prognostic air emission dispersion models were developed that could take over from models such as *Ausplume* when the situation required it. The more sophisticated models generated three-dimensional wind fields that evolved in time, using either prognostic wind models similar to numerical weather prediction models, or diagnostic models based on field data. These models drove puff or particle tracking models that simulated the advection and diffusion of airborne contaminants in the wind fields.

Regulatory authorities now require that emission dispersion modelling be carried out to underpin development applications involving air emissions, and significant confidence is placed in decisions based on such modelling.

Unfortunately, no comparable improvements have been achieved in the case of road traffic noise prediction modelling. Regulatory authorities are thus unable to require road traffic noise modelling for complex situations, and to a significant extent do not place great faith in the predictions of models such as TNOISE or STAMSON. In Australia at least a common consequence of this situation is that the noise impact for proposed developments is simply not properly assessed, which is the motivation for this research.

Typical Modelling Applications

STAMSON and TNOISE perform reasonably well in relatively simple situations. "Simple" means that the road, building and barrier geometries are straightforward; the terrain is fairly flat and uniform; the distance from the traffic to the sensitive usage (i.e. the prediction distance) is in the range of 15m to about 100m; and the traffic flow is well defined.

To illustrate such applications, actual traffic noise level measurements were compared to noise level predictions made using STAMSON at two sites adjacent to the two-lane Midland Highway near Pontville, some 25 km north of Hobart in southern Tasmania. Figure 3.3 shows a photograph of Site A: the road is level and its bitumen surface is in good condition. A virtually unrestricted view of the traffic flow was available in both directions (i.e. a 180° view) with no ground cover and closely-packed earth between the monitoring points and the road. The posted speed limit was 100 km/h.

Figure 3.3 Site A showing a situation with simple road geometry and terrain.

Figure 3.4 shows Site B, a slightly more complex site with traffic restricted to a posted speed limit of 60 km/h, changes in both the vertical and horizontal highway alignment, and sloping near-road terrain.

Figure 3.4 Site B showing a situation with more complex road geometry and terrain.

Sound pressure level measurements were made using two Acoustic Research Laboratories EL-215 noise level recorders, placed at distances of 15 m and 30 m from the road verge. Mr Shao Ng, a University of Tasmania PhD candidate, assisted the exercise by recording the number and classification of vehicles during each 10 minute noise measurement period. An appropriate traffic speed was estimated by timing selected vehicles as they travelled over a measured distance and averaging the speed of these vehicles.

The geometries of the two sites were modelled using STAMSON, and L_{eq} (1 hour) traffic noise predictions were made for the two measurement locations and the observed traffic conditions. Table 3.1 compares the L_{eq} (1 hour) model predictions to the L_{eq} (10 min) measurements, under the assumption that L_{eq} (1 hour) = L_{eq} (10 min) provided that the traffic flow characteristics over the 10 minute period are the same as over a one hour period, which is a common assumption in highway noise measurement work.

Table 3.1 shows that the STAMSON predictions are in reasonable agreement with the measured noise levels for these sites. This gives credibility to follow-on exercises such as examining the effect of increasing traffic, installing an acoustic barrier, changing posted speed limits, and making predictions that consider the effect of a proposed development.

	Light vehicles	Medium vehicles	Heavy vehicles	Speed km/h	dBA Measured	dBA Predicted
Site A	38	3	2	83	58	59
Site A	95	4	6	90	62	61
Site A	78	2	3	75	60	63
Site A	64	3	7	69	62	61
Site A	62	3	9	86	62	62
Site A	79	0	3	72	59	61
Site B	85	3	2	66	57	57
Site B	75	2	6	63	60	57
Site B	77	5	1	67	57	57

Table 3.1 - Summary of tests at Pontville and environs

Figure 3.5 shows a site involving barriers for a situation which is sufficiently straightforward that road traffic noise model predictions agree with measurements. A wooden barrier has been erected along the far side of the road to protect those residences most exposed to noise. An earth berm forms a barrier on the near side of the road. [Earth berms are more effective if the berm material is loosely packed rather than tamped down. The overall effect is for better ground attenuation of noise with the looser material.]

Figure 3.5 A simple situation involving an earth berm and wooden noise barrier.

Only very straightforward barrier effects can be handled by STAMSON and TNOISE, with the overall prediction summing the component predictions for sections of the road which the receiver can still see, and sections of the road which lies along the line of sight of the barrier. The required inputs are the barrier height; distance and elevation with respect to the road; and the angles defining the section of road beyond the barrier.

Problematic Modelling Situations

At more complex sites, such as that shown in Figure 3.6, the road traffic modelling exercise becomes more difficult. Figure 3.6 shows a road near Hobart in southern Tasmania, featuring traffic flows along a dual carriageway, a slip road, and an overpass; combined with the presence of earth berms, housing and variable terrain. The traffic noise emissions from the road and overpass are in direct line of sight with some houses to the left of the photograph, and are not attenuated by the earth barrier on the slip road.

Figure 3.6 A site that is beyond the ability of present traffic noise models to address.

There is only very poor agreement between noise model predictions and measurements for such sites. Experience shows that the usefulness of a road traffic noise model in such situations is severely limited, essentially providing only an indication of how much noise levels may change by if, for example, traffic flow were to increase by a certain amount.

Nevertheless, the degree of complexity in the situation shown in Figure 3.6 is quite commonly encountered during noise impact assessment work. It is frustration at not having adequate modelling tools for such situations that has motivated the present research.

4.0 NEURAL NETWORKS FOR SIMPLE SITUATIONS

4.1 Motivation

As outlined in the introduction, the author discussed the problem of how to develop road traffic noise prediction models able to deal with reasonably complex situations with a fellow environmental professional, Dr Steve Carter, who suggested that a way forward might be to develop road noise prediction models based on neural networks.

The motivation for this suggestion is an appreciation that existing road traffic noise prediction models, such as TNOISE, are largely empirical in nature. As explained in Chapter 3, a given noise level prediction results from applying a logarithmic summation to a set of component numbers, each of which is empirical in nature. The reference noise level, at 15m from the road side in the case of STAMSON, is an empirically determined function of the type of vehicle and its speed, which is a linear relationship in log space. Adjustments to the reference noise level are also empirical in nature. For example, the distance adjustment is made on the basis of someone measuring the variation of noise level with distance from a road, and producing a graph or table of this variation for a given type of ground cover (absorptive or reflective), which can be hard-coded into the computer model.

The fact that the noise vs distance relationship is sufficiently simple that it can easily be represented by an equation, as discussed in Chapter 3, does not alter the fact that the relationship was determined by a pattern recognition exercise. The governing equation was determined as a best-fit to the data; and in the case of barrier effect adjustments the relationship between noise levels and barrier characteristics is not so easily parameterised.

The appreciation that present road traffic noise prediction models are pattern recognition tools is both a blessing and a curse. The blessing is that model predictions are guaranteed to agree with noise measurements if the situation corresponds to the conditions under which the reference noise level and various adjustments were determined, and assuming that such effects sum according to the mathematics of logarithmic addition.

The curse is that there are many ways in which modelling situation can become too complicated for present road traffic noise models. For example, road traffic noise levels at a given prediction location may be significantly influenced by reflections from one or more building facades, the combined influence of multiple roads, barriers placed at angles to a road, variable terrain elevations, and so on: and an impossibly large number of empirically determined adjustments would be needed to enable a single model to satisfactorily address the myriad possible combinations of such factors. In addition, the models are not able to account for factors such as a predominance of one kind of heavy vehicle instead of the assumed mix of heavy vehicle types.

This is the fundamental reason for lack of progress in extending the road traffic noise prediction models developed in the 1980s to more complex situations. Although the basic principles of acoustic physics are well understood, in practice the situation is a highly challenging modelling exercise, such that no road traffic noise prediction model based on theory – the equivalent of the numerical wind models developed to advance the practice of air dispersion modelling – has yet been developed.

Artificial neural networks, one of the three principal tools of artificial intelligence (the others being expert systems and genetic algorithms) are also pattern recognition tools. They provide a powerful and elegant way of finding patterns in data, and there was little doubt that a neural network approach to road traffic noise prediction could reproduce the work of models such as TNOISE, and this chapter examines the architecture and data input requirements of a neural network appropriate for this task.

Two exciting possibilities are immediately apparent. The first is that a neural network approach to modelling road traffic noise may provide an improved modelling capability for the fairly simple situations that the present models do not always handle well. Chapter 5 discusses reasons for this problem, and provides a site-specific example that demonstrates the power of an alternative approach using a neural network.

Second, neural networks can easily handle 2-dimensional data, which suggests that they may be able to provide a way of handling the more complex road traffic noise prediction situations that are beyond the capability of present models. Chapter 6 examines how this might be done.

4.2 Review of Previous Work

Numerous publications discuss the use of artificial intelligence tools in areas of road traffic engineering other than traffic noise prediction. For example, Carter et al. (2000) used a combination of image processing and neural networks in their demonstration automated multiple-lane traffic survey system that analysed real-time feed from cameras used to monitor traffic on the main roads through Hobart, Tasmania. Expert systems, which are decision-making tools, have long found application in controlling traffic lights.

Considering road traffic noise, the author's employment by the Tasmanian State Government brought him into regular contact with acousticians working for regulatory authorities in other Australian jurisdictions, for example by participating in initiatives to develop legislation and methodologies relating to noise. Through to his retirement in 2001, the possibility of using artificial intelligence tools in road traffic noise prediction – or in any other acoustics context – was never raised, even informally.

Literature reviews carried out in 2003 and 2007 concluded that there has been little research into the use of neural networks to predict traffic noise, and apparently no work that directly aligns with the research presented in this thesis, namely study of the possibility that neural networks might offer a way to improve on existing road traffic noise prediction models.

Cammarata et al. (1993) used a neural network approach to examine functional relationships between road traffic noise and physical parameters in an urban context, and they concluded that neural networks could be used to model noise in urban areas. This was verified by the work of Mallawany et al. (1999), who successfully applied a neural network to predict the bulk traffic noise in Cairo.

There appear to have been no follow-up applications of neural networks to predict urban noise levels, although Avşar et.al. (2004) used a neural network to determine the pattern of noise measurements made at 16 locations within a University campus, with the inputs being the location of the measurement station, various meteorological data, and the time of day. However, the correlation between noise predictions and measurements was only about 0.69, presumably because this work appears to have assumed that the time of day could be used as a fingerprint for variation in the noise produced by traffic on adjacent roads, and variation in on-campus noise sources, which is likely only true at first-pass.

4.3 The Nature of Neural Networks

Artificial neural networks have been successfully applied to many engineering problems involving pattern recognition, facilitated by technical computing software packages such as *Matlab*, with little competition from classical pattern recognition methods such as regression analysis. Learning about neural networks is a standard part of undergraduate engineering degree courses, and the reader is referred to texts such as Demuth et al. (2006) and Negnevitsky (2003) for details. The other principal artificial intelligence tools are expert systems, used for decision making; and genetic algorithms, used for optimisation exercises.

A neural network approach is appropriate when there is a pattern contained in a data set, but the pattern is not easily described using conventional mathematics. Applications such as speech and face recognition are well known. In the case of road traffic noise, the relationship between the data that describe a given situation and the associated noise levels could only be described in a satisfactory way using the governing physics equations by a sophisticated numerical model developed using computational fluid dynamics.

An artificial neural network mimics the operation of a human brain, which is a biological neural network that consists of highly connected layers of data processing units called neurons. Figure 4.1 depicts a typical neuron in the brain. The cell has a central nucleus that stores information, and dendrites carry a signal into the cell where it is processed. The axon then carries the processed signal away to the relevant area in the body. Figure 4.2 shows an artificial neural network which consists of layers of artificial neurons, each of which is a data processing unit that mimics the function of a brain's biological neuron.

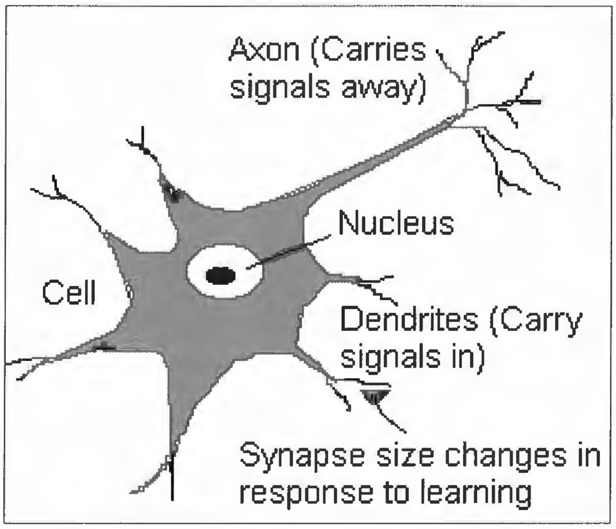


Figure 4.1 A Biological Neuron.

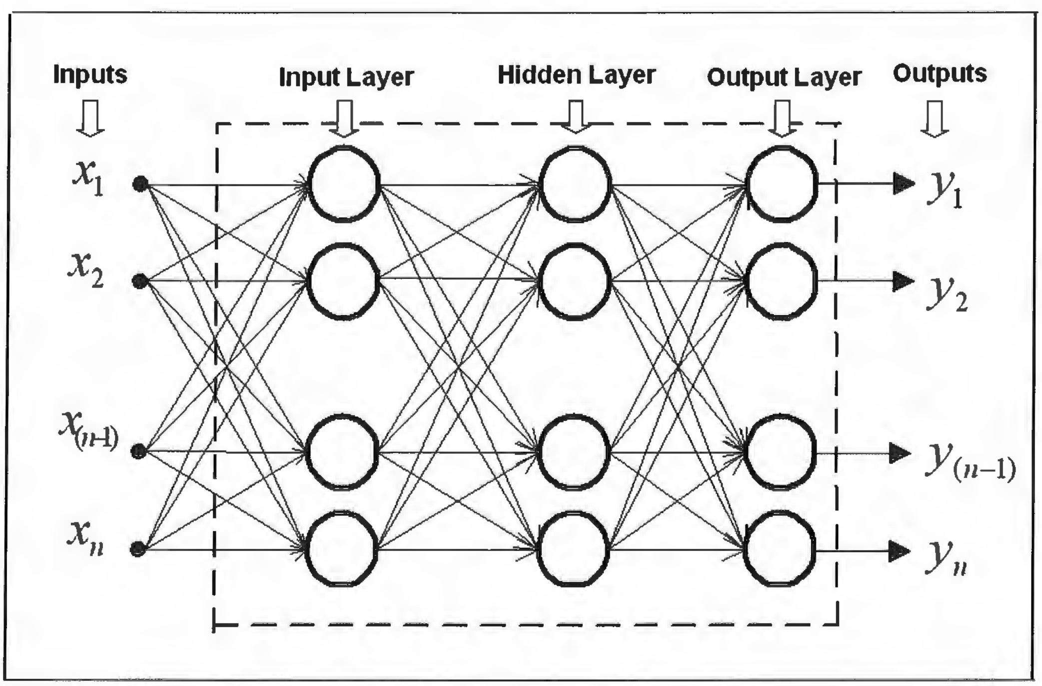


Figure 4.2 **An artificial neural network, with the circles depicting neurons. Each vertical set of neurons constitutes a layer of neurons, and in general each neuron layer consists of different numbers and types of neurons.**

Figure 4.3 shows the operation of a single (artificial) neuron. The neuron receives a set of signals (x_i) which, as can be seen from Figure 4.2, are either the set of input data values, or the set of output signals from the previous layer of neurons. The neuron applies weight w_i to each input x_i, sums the weighted signals, adds a bias (b) to the result, and produces its own output signal, y, according to a "transfer function", f.

$$y = f\left(\sum \omega_i x_i + b\right)$$

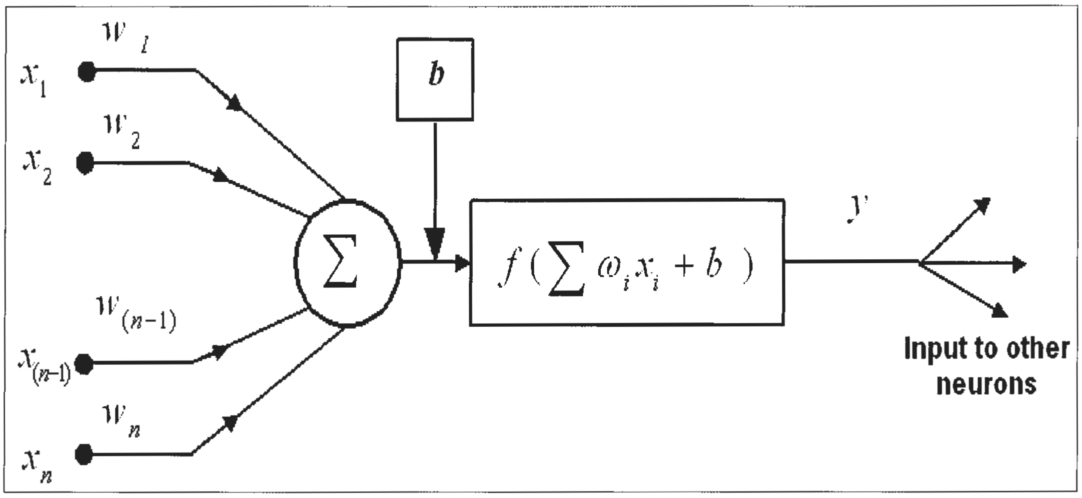


Figure 4.3 Operation of a neuron.

A neural network's *architecture* refers to the number of neuron layers, the number of neurons in each layer, and the types of transfer functions used by the neurons in each layer. The transfer function specified for the neurons in a given layer depends on the nature of the problem. Common choices include sigmoidal, linear, and step functions.

Producing a neural network architecture appropriate to the task at hand is considered to be half-art and half-science, and one goal of this chapter is to determine an architecture that is appropriate for road traffic noise prediction work.

In many ways, a neural network is very similar to a regression model. Both approaches to modelling patterns in data require a training data set that provides examples of the output associated with a given set of input data, and more complex patterns require more training data records. Both approaches require an algorithm that adjusts the free parameters of the neural network, or the fitting function in the case of a regression analysis.

A regression analysis data fitting function has free parameters that are adjusted to best-fit the function to the data. For example, the gradient and intercept of a straight line can be adjusted using a least-squares method to best-fit the straight line to a set of data.

In the case of a neural network, there is no need to specify the function to be fitted to the data, since the free parameters consist of the weights and biases associated with all the neurons in the network. This is a far greater number of free parameters than might define a classical best-fit function applied to a regression analysis, and hence the untrained neural network is essentially a blank template for *any* fitting function. Also, the high degree of connectivity between the neuron enables much more complex and non-linear patterns to be identified in data; and, like a regression model, a trained neural network can generalise to predict the output associated with input data that were not part of the training set.

Overall, an artificial neural network is still a very long way from having the sophistication of a biological neural network, but it is a masterpiece of biomimicry whose power and range of applicability is only now becoming appreciated as computing power and software facilitates such applications.

4.4 A Neural Network for Road Noise Prediction

Network Architecture

A two-layer feed-forward neural network is proposed for simple road traffic noise prediction situations, such as those for which models like *Stamson* are appropriate, and as discussed in Chapter 3. *Feed-forward* refers to the one-way propagation of information from the first (input) layer of neurons to the last (output) layer. A rule-of-thumb in designing a neural network's architecture is to match the complexity of the neural network to the pattern recognition task. Road traffic noise prediction is a straightforward task: the predictive power associated with hidden layers of neurons is not needed, while experimentation found that an input layer with 20-30 neurons was sufficient for the exercise. A tangent-sigmoidal transfer function was specified for the input layer neurons, as shown in Figure 4.4.

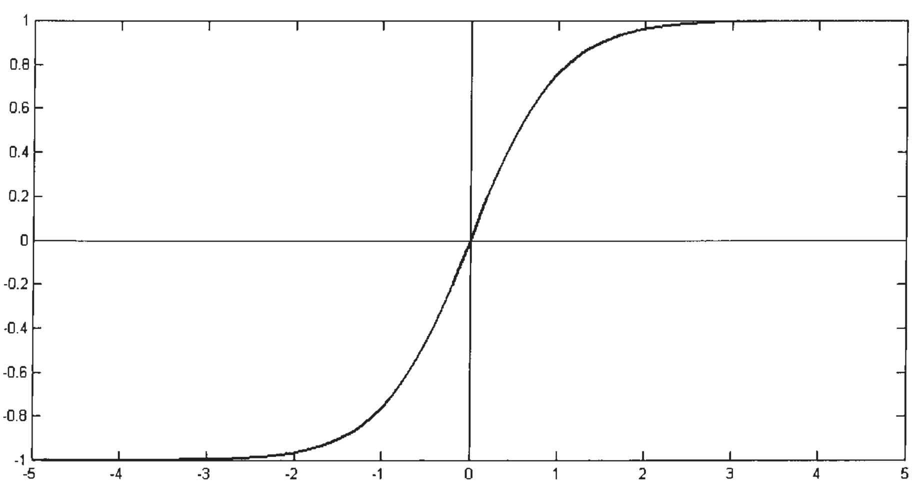


Figure 4.4 Tangent-sigmoidal transfer function. Output range is ±1.

The range of effective input values for this transfer function is roughly-3 to +3, and its output range is ±1. As noted, the input to the transfer function is the sum of the weighted input values plus a bias, and the neuron can adjust the weights, w_i , applied to the inputs to incorporate an overall scaling factor, α , such that $w_i \rightarrow \alpha\, w_i$. Together with appropriate adjustment of the bias this results in the inputs to the transfer function having the required range of ±3. However, a priori rescaling of input values to roughly match the requirements of the transfer function facilitates the neural network training. For the present noise prediction exercise, the vehicle speeds are typically up to 100 km/h, and hence are divided by a factor of 50 ahead of being presented to the neural network.

Considering next the output layer of neurons, the number of neurons in this layer must equal the number of output variables, in this case just one: the equivalent sound level, L_{eq} (1 hour). A linear transfer function was prescribed for this single output neuron.

Training Data

Consider the exercise of predicting equivalent sound levels (L_{eq} values) due to road traffic, at distances between 20 m and 200 m from the road, and for speed limits between 50 km/h and 100 km/h. Assume that all other parameters, such as traffic composition, are constant, and that the receiver has an uninterrupted view of the road. Figure 4.5 shows the L_{eq} surface, predicted by STAMSON, mapped out by this range of distance and speed parameters.

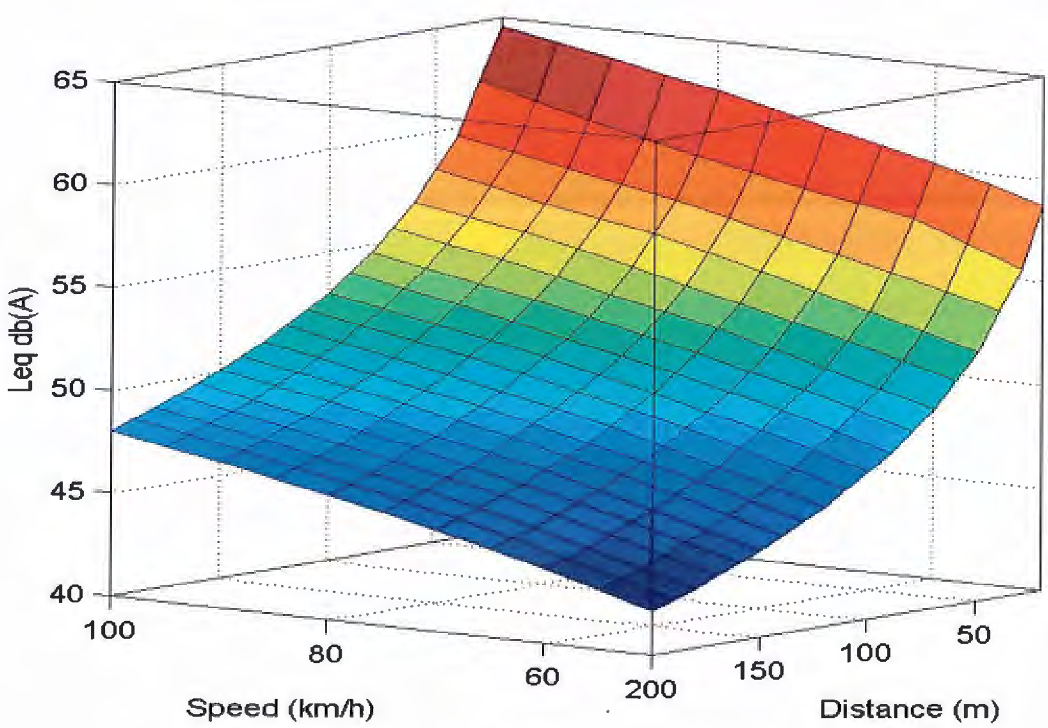


Figure 4.5 L_{eq} noise level variation with speed and distance.

The physics of sound is naturally described by the mathematics of logarithmic quantities, as discussed in Chapters 2 and 3. In particular, sound levels have a logarithmic dependence on both vehicle speed and distance from the road, and adjustments for other sound propagation effects are also usually logarithmic in nature. Figure 4.6 shows this dependence by replotting the sound level surface of Figure 4.5 on a log-log scale, whereby it becomes a simple plane.

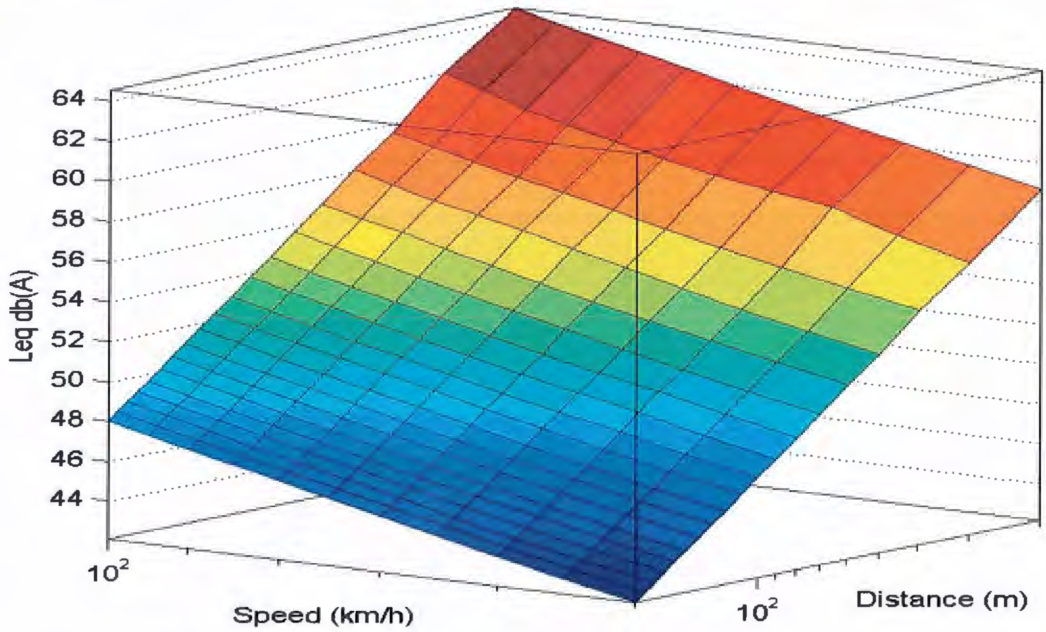


Figure 4.6 Log-log plot of the above L_{eq} noise level variation.

It is tempting to linearise the modelling exercise by using logarithmic input variables, since a pattern represented by a plane needs only three points to be defined. However, to demonstrate a neural network's ability to recognise non-linear patterns in data, conventional input variable values are retained.

Since the pattern recognition task is in non-linear form, a key question is how much data are needed to train the neural network. It is not sufficient that a neural network is only able to correctly produce the outputs (L_{eq} values) corresponding to the training data: it must be able to generalise to new data.

In this case, it was found that 39 training data records were sufficient to define the surface in Figure 4.5, and hence enable the neural network to be properly trained. Table 4.1 shows L_{eq} values for three vehicle speeds and six road-receiver distances. The overall input data set included additional L_{eq} values for vehicle speeds of 50, 70 and 90 km/h, at receiver set backs from the road of 30, 50, 70, 90, 120, 150, and 200 m.

	60 km/h	80 km/h	100 km/h
20 m	60.16	62.60	64.56
40 m	55.18	57.62	59.58
60 m	52.26	54.70	56.67
100 m	48.59	51.03	53.00
140 m	46.17	48.61	50.58
200 m	43.61	46.05	48.01

Table 4.1 18 of the 39 neural network training data records generated by the STAMSON model. The shaded values are the L_{eq} (1h) noise levels (dBA) for the given traffic speed and distance of the receiver from the road.

Network Training

A *backpropagation* algorithm, *traingdx,* was used to train the neural network, whose Matlab implementation is described by Demuth et al. (2006). Backpropagation network training is a commonly used error gradient descent technique, and for this exercise it was used with momentum and an adaptive learning rate.

An error gradient training approach means that the neuron weights and biases are adjusted to give the most rapid reduction in the sum-squared error between the network's actual output and its required output (i.e. the predicted verses required L_{eq} values).

The momentum parameter allows the network training to overcome localised minima in the sum-squared error surface. When the network's weights and biases are such that its predictions are in a localised minimum in error space, small adjustments to the weights and bias of a neuron result in an increase in sum-squared error, but larger adjustments again result in a decrease in the sum-squared error. The adaptive learning rate adjusts the training algorithm to make larger adjustments to the weights and biases if the sum-squared error surface is relatively smooth.

The neural network training was carried out in "batch mode", whereby the neural network's noise level predictions for all 39 combinations of posted speed limit and receiver distance from the road are compared to the target values produced by STAMSON. Based on an overall comparison of the neural network predictions to the required target values, the training algorithm then adjusts the neuron signal weights and biases across the network, working backward from the output layer (hence "backpropagation"). The neural network makes a new set of predictions for all the training records, and the process is repeated.

Each such iteration, known as a training epoch, results in a new set of predictions, and Figure 4.7 shows a typical training progress graph.

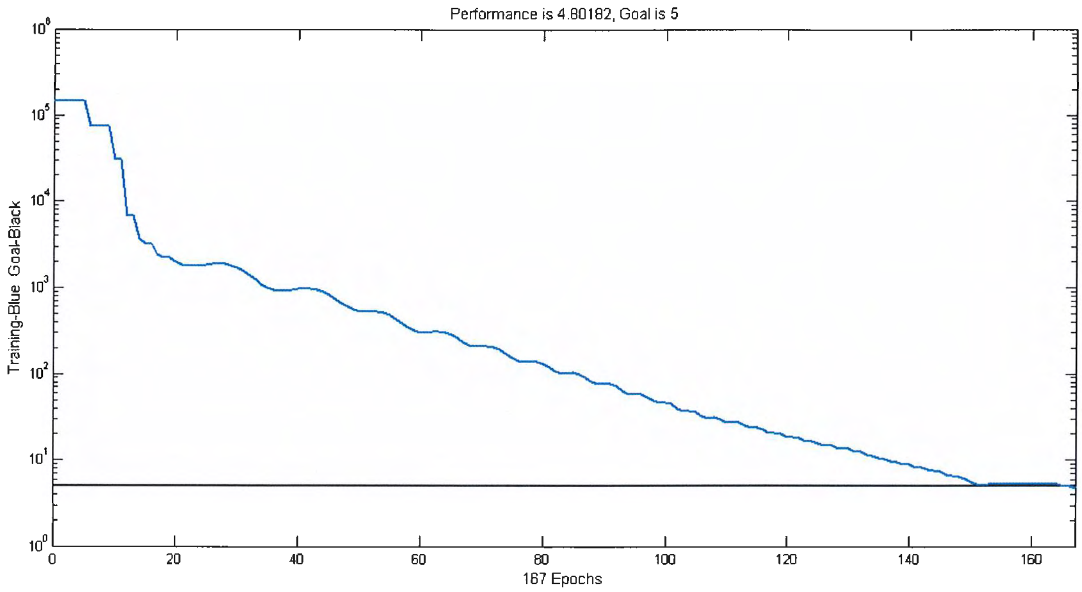


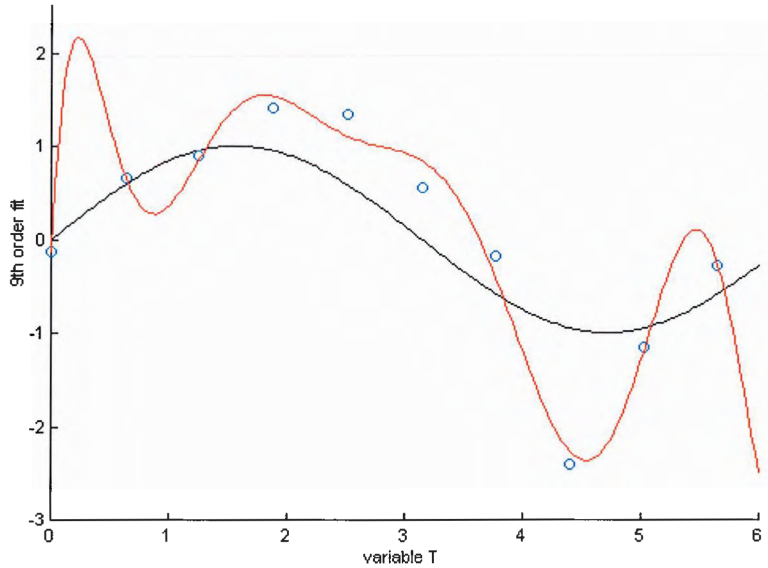
Figure 4.7 A neural network training performance graph. See text for discussion.

In Figure 4.7, the descending blue line charts the reduction in sum-square error (SSE) as the training proceeds through about 150 training epochs. The SSE is the sum of the squares of the residuals, which are the differences between the target and predicted values. The initially high SSE simply corresponds to initialisation of the neural network's weights and biases at reasonable values, and the early training epochs rapidly reduce the SSE, such that it is appropriate to plot the SSE on a log scale in the training progress graph.

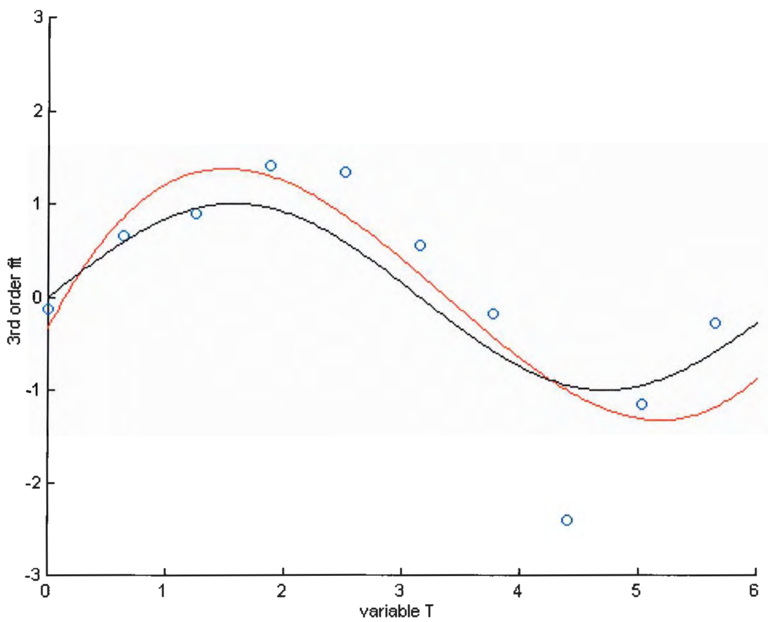
Overfitting can prevent a neural network from properly generalising to produce sensible predictions from input data other than the training data. The classical case of overfitting a polynomial curve to data is shown in Figure 4.8, which illustrates an exercise discussed by Bishop (1995). Data are produced by sampling a sinusoidal function, and using a random number to generate noise. Cubic and 9th order polynomials are then fitted to the noisy data.

In Figure 4.8, the high order polynomial tracks the sample data more closely than the cubic polynomial, but the cubic polynomial better models the systematic aspect of the data (the sinusoidal function). The low order polynomial thus generalises better to new data, while the higher order polynomial is said to overfit the data.

Similar behaviour can occur with neural networks, especially if a relatively large number of neurons and/or neuron layers has been specified compared to the complexity of the data and the pattern contained in the data. This leads to the rule-of-thumb noted above that a neural network's architecture should be matched to the problem to hand, one guide to this being that it typically takes several attempts to successfully train the network.



Ninth order polynomial fit to data



Cubic polynomial fit to same data.

Figure 4.8 **3^{rd} and 9^{th} order polynomial fits (red lines) to noisy data (blue circles) based on a sine function (black line). The high order polynomial is overfitting the data, while the low order polynomial correctly tracks the sine function.**

A good way to avoid overfitting is to examine the neural network model predictions for a second, validation, input data set. Initially, the sum-squared error values between predicted and target values decreases for both the training data set and the validation data set. Training is stopped when the SSE for the validation data set starts to rise, indicating that overfitting is starting to be a problem.

4.5 Neural Network Performance

Figure 4.9 shows the equivalent sound level (L_{eq}) values predicted by the neural network over the 50-100 km/h speed range and the 20-200 m road-receiver distance ranges. Clearly, the neural network has correctly identified the relationship between L_{eq} values, speed and distance.

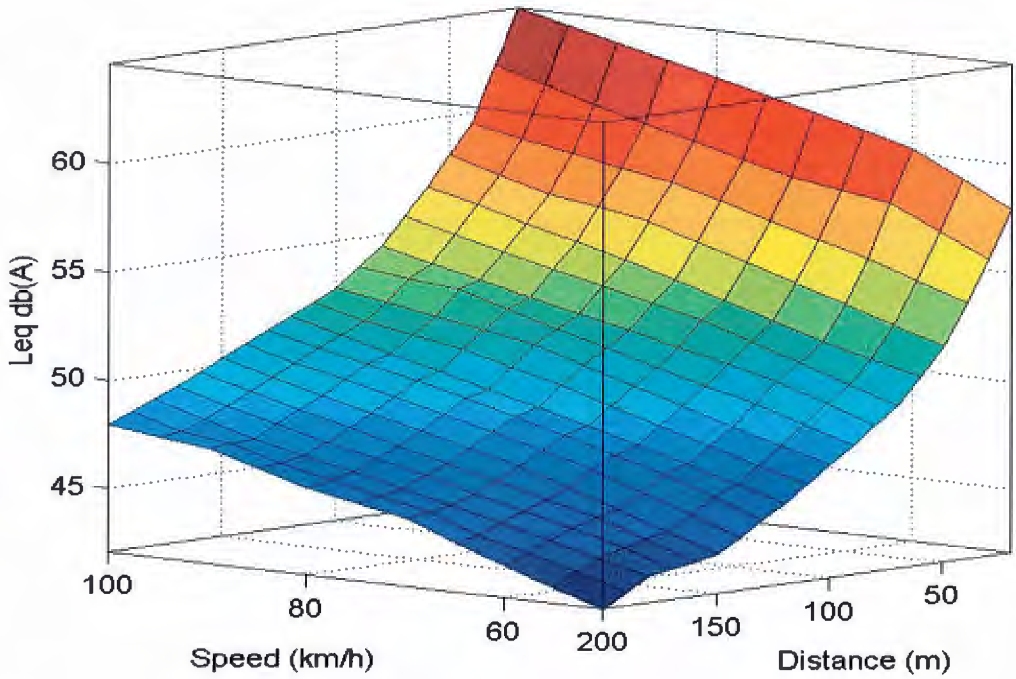


Figure 4.9 Neural net L_{eq} predictions (compare to Figure 4.5)

In Figure 4.9, the wrinkles in the predicted L_{eq} surface are minor, and can be used as a guide to which new records (i.e. distance, speed, and L_{eq} values) should be added to the training data set to improve the neural network's performance. For example, the wrinkles are mainly associated with low (50 km/h) speed traffic, and consideration of Table 4.1 shows that the lowest speed in the training data was 60 km/h. Therefore adding some records of L_{eq} values for speeds lower than 60 km/h should remove these wrinkles.

Figure 4.10 compares STAMSON L_{eq} sound levels (solid line) to the neural network L_{eq} predictions (dashed line) for a traffic speed of 70 km/h. There is clearly good agreement between the two modelling approaches.

In conclusion, a simple feed-forward neural network is easily able to mimic a conventional road noise prediction model. The exercise presented in this chapter used L_{eq} sound level values produced by STAMSON to train the neural network, but this is of course no different from selecting L_{eq} sound level values from the empirical data on which STAMSON is based.

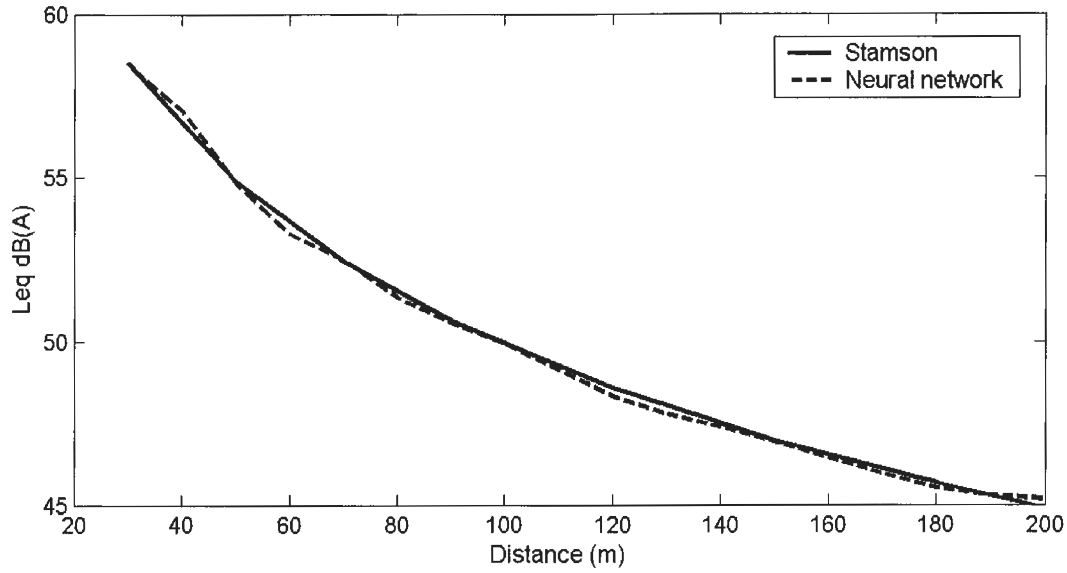


Figure 4.10 Stamson vs neural net L_{eq} predictions for a traffic speed of 70 km/h.

The demonstration exercise was restricted to consideration of L_{eq} predictions for only two variables, namely traffic speed and distance from the road. Neural networks are well understood, and their ability to successfully carry out this simple pattern recognition task was never in doubt, such that the main goal of the exercise was to determine an appropriate neural network architecture and to determine roughly how many data records are needed to train the neural network. An extension of the neural network to L_{eq} predictions based on additional variables, such as traffic composition and traffic volume, would involve an essentially identical process of normalising the input data to the effective range of the tangent-sigmoidal transfer function, and experimenting with the amount of input data records and the number of neurons (perhaps adding a hidden layer of neurons) until satisfactory predictive performance is achieved.

5.0 CASE STUDY: THE HAMPSHIRE MILL PROJECT

5.1 The Need for Better One-Dimension Models

Present road traffic noise prediction models are essentially tools that combine empirically established patterns in one-dimensional data, namely the variation of noise levels with distance from a road under various conditions, such as elevation differences and ground type. They can consider two-dimensional effects, such as the effect of multiple roads, or the variation of noise levels in the presence of a barrier that partly blocks line of sight to a road, but they only do so by breaking the calculation into component one-dimensional situations and summing the component predictions.

Neural networks have a proven ability to model patterns in two-dimensional data, such as images or data that are referred to map coordinates. This motivates examination in Chapter 6 of whether a neural network can provide a better way to model two-dimensional situations that are too complex to be decomposed into component one-dimensional calculations. Ahead of that, this chapter demonstrates the exciting possibility that a neural network that is able to mimic STAMSON or TNOISE, as described in Chapter 4, can go beyond the range of application of these existing models in the one-dimensional situations for which the models were developed.

The author has noticed that the passing years have found progressively less agreement between road traffic model predictions and noise measurements, presumably because the empirical reference noise levels that are hard-coded into the present road traffic noise models were determined by measuring noise from vehicles built in the 1960s - 1980s, and these reference noise level equations may be incorrect for various reasons. First, 2007 vehicle designs are different from older vehicle designs. For example, B-double trucks are recent additions to the vehicle fleet, and the aerodynamic shield on top of prime movers is also a comparatively recent development. Second, situations that seem to be common in Tasmania – including the one presented in this case study - involve a large number of specific heavy vehicles, such as log trucks or wood chip trucks, instead of the more blended mix of heavy vehicle types that would be expected on, say, a national highway.

Third, noise emissions from the 2007 vehicle fleet are generally lower than for the vehicle fleets of past years. The Australian Design Rules (ADRs) specify maximum noise emission levels for all classes of vehicles, and the ADRs are regularly reviewed, with one goal being to harmonise with European vehicle standards. The current standard is *Vehicle Standard (Australian Design Rule 83/00 External Noise) 2005.*

Another problem with present road traffic noise models is that they are unable to make predictions inside the reference distance from the road, or for low traffic flows (15 m and 40 vehicles/hour respectively for STAMSON). Unfortunately, many residential developments in Tasmania lie within this reference distance, while early morning heavy vehicle traffic often triggers noise nuisance complaints even though the number of vehicles involved is low.

The author considers that the 1993 Hampshire Project in north-west Tasmania was problematic for road traffic noise prediction models for several of the above reasons. These were frustrating problems at the time, and 14 years later it is a pleasure at last to have developed a way to overcome these difficulties.

5.2 Overview of the Hampshire Project

In 1993, Associated Pulp & Paper Mills (APPM) proposed to establish a wood chip mill on a greenfield site at Hampshire, about 27 km south of Burnie in north-west Tasmania. The application for approval of the proposed development was supported by a study of the possible transport routes for delivering timber to the mill from areas in the north and west of Tasmania by wood chip trucks. Concerns regarding the impact of noise nuisance from heavy vehicle traffic focused on residences along the B17 secondary road from Burnie to Hampshire. Figure 5.1 shows the northern section of this route, from Burnie to Ridgely with the 14 km of road between Ridgely and Hampshire having very few residences.

The Development Proposal and supporting Environmental Management Plan (DPEMP) for the proposed woodchip mill was prepared by Tasmanian consulting firm Environmental & Technical Services (E&TS, 1993). The maximum throughput of pulpwood was to be 1.25 million tonnes per year, and the project had major economic implications for north west Tasmania. Moving forward in time to 2007, most people would agree that the woodchip mill has been a successful venture, but at the time there were understandably many concerns raised about the proposal.

The DPEMP included an assessment of the impact that noise emissions from the increased heavy vehicle traffic would have on residences along the B17 road (E&TS, 1993). The annual average daily traffic (AADT) in 1992 through Ridgely was 2825 vehicles, with heavy vehicles accounting for 17.9% of all traffic. This is significantly higher than the usual percentage of heavy vehicles on a rural road, and was explained by that fact that the road was already used by a large number of log trucks. It was expected that most of these log vehicles would be replaced by wood chip trucks after the woodchip mill was constructed, with a modest overall increase in heavy vehicle traffic of ~30%, to just over 200 return trips a day, depending on details of the transport strategy.

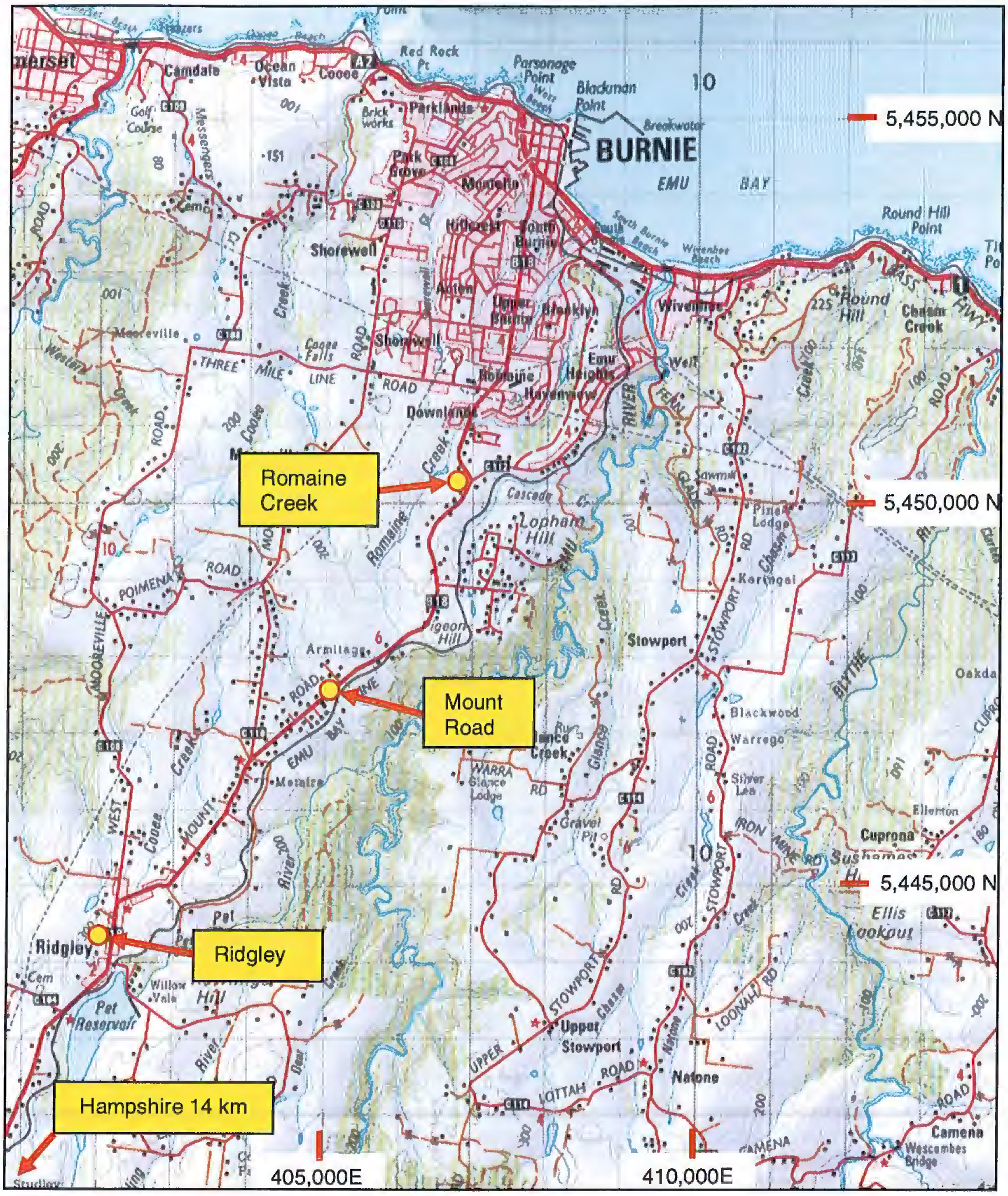


Figure 5.1 Site location map. Burnie is on the north-west coast of Tasmania.

At the time, in 1993, the author was employed by the Tasmanian State Government as an acoustics specialist, and Mr Jim Stephens of E&TS carried out his firm's noise assessment assignment in consultation with me. We agreed a program of continuous 24 hour traffic noise measurements, supported by records of traffic volumes and vehicle types. The author is indebted to Mr Stephens, who has now retired, and to the State Government for permission to use the data gathered during this exercise for the purpose of this case study.

The Hampshire project makes an ideal case study, because the noise measurement program gathered data that spanned a large range of vehicle numbers and classifications, and hence noise levels. This is crucial, because it allows a neural network to be trained properly. A noise measurement program that targets only worst case noise levels produces data that all relate to high noise levels, which does not provide a suitable training data set.

This case study illustrates how a project-specific road traffic noise prediction model can be produced using a neural network approach, and in particular the distances from the road to the receivers were less than 10 m at all noise measurement sites, which precluded the use of road traffic noise prediction models, such as STAMSON and TNOISE.

5.3 Noise Monitoring Site Descriptions

Four sites were chosen for traffic noise monitoring purposes in the original investigation. However, only data from three of the sites are used for the present case study, because these three sites were quite similar in terms of their site geometry, road–receiver distances, and posted speed limits, while the fourth site was somewhat different. The road was surfaced by good condition bitumen at all three sites.

Ridgley

As shown in Figure 5.2, the Ridgley noise monitoring site is in a residential area located on the main street of Ridgley township. The road gradient is ~4% and the posted speed limit is 60 km/h. North-bound traffic from Hampshire travels up hill at this location, while traffic from Burnie travels downhill. The noise logger was located 4.5 m from the road verge.

Figure 5.2 Ridgley road noise monitoring site

Mount Road

Figure 5.3 shows the Mount Road site, roughly half way between Ridgley and Burnie. The ground is gently sloping on either side of the road with residences close by, and vehicles entering and leaving the properties throughout the day. The posted speed limit is 80 km/h. The noise logger was located 6.5 m from the road verge.

Figure 5.3 Mount Road Site.

Romaine Creek

The Romaine Creek site is located about 1 km south of Burnie, on Mount Road immediately prior to its intersection with Old Surrey Road. The monitoring site at 5.3 m from the road verge is at the end of an 80 km/h posted speed limit zone, prior to a 60 km/h zone which includes the nearby intersection with traffic islands. Significant noise was heard at this site that was associated with vehicles slowing or accelerating.

Figure 5.4 Romaine Creek Site

5.4 Noise Measurements

The test period covered 24 hours commencing at 0600 hours and carrying on over one hour periods until the same time the following day. This facilitated comparison of the measured noise levels to standards written in terms of different averaging periods (see Chapter 2). It also provided an opportunity to establish early morning traffic noise data, since early morning traffic often provokes complaints of noise nuisance.

A Bruel & Kjaer (B&K) Type 2231 sound level meter was used at the Ridgley and Mount Road sites. At the Romaine Creek site, a B&K Type 4426 and a B&K Type 4435 meter were set up in tandem. The instruments were calibrated before and after the noise measurement program in the standard manner, with no significant calibration drift. The microphones were mounted at a height of 1.2 m, oriented at 90° to the road, and roughly parallel to the ground.

The vehicle classifications were:

- **Light vehicles** consisted of cars, utilities, four wheel drive vehicles, and motorbikes.
- **Medium vehicles** were defined as vehicles with two axles and capable of carrying a load of about one tonne of material.
- **Heavy vehicles** were defined as vehicles with more than two axles.

Actual vehicle speeds were not measured. The results of the noise measurements are summarised in Table 5.1 to 5.3.

Table 5.1 Ridgely Site noise measurements.

	Vehicle counts			
Time	Light	Medium	Heavy	Leq (1h) dBA
0600-0700	125	5	39	69.4
0700-0800	147	12	46	70.8
0800-0900	144	17	45	71.3
0900-1000	168	21	46	70.9
1000-1100	185	13	52	70.4
1100-1200	156	11	42	70.2
1200-1300	169	13	45	70.1
1300-1400	163	12	48	71.0
1400-1500	162	20	57	71.5
1500-1600	176	25	49	70.8
1600-1700	280	15	37	71.7
1700-1800	273	12	20	70.5
1800-1900	182	2	15	68.1
1900-2000	115	3	7	67.3
2000-2100	80	0	7	65.0
2100-2200	77	1	3	63.4
2200-2300	63	2	1	63.6
2300-0000	22	0	0	56.8
0000-0100	17	1	0	57.5
0100-0200	9	0	2	57.1
0200-0300	5	1	0	51.0
0300-0400	4	0	1	55.5
0400-0500	6	2	13	62.2
0500-0600	28	1	37	68

Table 5.2 Mount Road Site noise measurements.

	Vehicle counts			
Time	Light	Medium	Heavy	Leq (1h) dBA
0600-0700	69	9	32	69.9
0700-0800	144	14	48	75.0
0800-0900	118	30	54	76.7
0900-1000	104	20	43	66.4
1000-1100	127	7	47	66.2
1100-1200	117	14	42	65.6
1200-1300	147	8	42	66.4
1300-1400	141	11	46	66.2
1400-1500	140	22	53	66.2
1500-1600	162	13	47	67.0
1600-1700	213	11	35	67.2

Continued...				
1700-1800	247	17	26	66.7
1800-1900	118	1	15	65.1
1900-2000	93	10	7	63.3
2000-2100	65	7	7	63.0
2100-2200	51	9	4	62.8
2200-2300	57	1	1	60.9
2300-0000	24	0	0	56.8
0000-0100	18	0	0	52.1
0100-0200	6	1	1	52.2
0200-0300	2	2	0	50.4
0300-0400	4	0	2	55.6
0400-0500	5	4	5	60.4
0500-0600	27	4	22	64.6

Table 5.3 Romaine Creek Site noise measurements.

		Vehicle counts		
Time	**Light**	**Medium**	**Heavy**	**Leq (1h) dBA**
0600-0700	101	9	36	68.5
0700-0800	185	13	47	71.1
0800-0900	207	30	51	71.1
0900-1000	165	19	42	69.5
1000-1100	160	17	50	69.9
1100-1200	159	14	48	69.1
1200-1300	186	9	45	70.3
1300-1400	160	19	46	69.9
1400-1500	172	33	51	70.8
1500-1600	220	26	44	70.9
1600-1700	264	19	31	71.6
1700-1800	289	19	27	70.9
1800-1900	173	6	14	69.1
1900-2000	151	4	9	68.1
2000-2100	115	0	5	67.1
2100-2200	82	1	5	65.7
2200-2300	74	1	1	64.8
2300-0000	30	1	1	58.9
0000-0100	13	2	0	59.8
0100-0200	8	1	1	55.6
0200-0300	2	2	0	53.9
0300-0400	5	0	1	60.2
0400-0500	7	3	6	59.9
0500-0600	39	0	20	67.3

5.5 Neural Network Model

Guided by the neural network architecture used for the preliminary modelling work reported in Chapter 4, a two-layer feed-forward neural network was used to model the measured noise data from the three Hampshire sites. The first (input) neuron layer contained 20 neurons with tangent-sigmoidal transfer functions, while the second (output) neuron layer contained a single neuron with a pure line transfer function. The neural network was trained using the backpropagation algorithm described in Chapter 4.

The Hampshire case study has the appeal of being a real life project, but the data gathered at each site are insufficient to train site specific neural networks, which in practice would be an obvious noise assessment strategy. The data were thus combined to produce an overall data set of 3 x 24 = 72 records, which were divided into a training data set of 56 records, and a check data set of 16 records. The training data were selected to span as wide a range as possible of traffic counts and measured L_{eq} (1 h) noise levels.

The neural network inputs were the light, medium and heavy vehicle traffic counts, although the number of medium vehicles observed each hour did not fluctuate much compared to the number of light and heavy vehicles. Actual vehicle speeds were not recorded, but the posted speed limits spanned the range 60 to 80 km/h, while road-receiver distances spanned the range 4.5 to 6.5 m from the road side. Neither vehicle speeds nor the road-receiver distance were provided as neural network inputs, since they were all so similar, which means that the neural network is unable to account for the influence of these factors on the pattern of measured L_{eq} (1 h) noise levels, and thus is not able to generalise to noise level predictions at different set backs from the road, or traffic speeds of, say, 100 km/h. However, the neural network is expected to provide a reasonable first-pass ability to predict L_{eq} (1 h) noise levels for this site-specific application.

As discussed in Chapter 4, the standard neural network training strategy is to monitor the sum-square-error of predictions vs actual noise levels for a validation data set (whose records are not part of the training data set), and terminate the neural network training when the sum-square-error for the validation data set starts to rise. However, for this case study, there were insufficient data records to enable a validation data set to be established, and the neural network training was thus terminated after some 200 epochs, as shown in Figure 5.5, corresponding to the start of the phase of network training in which a gradual reduction of sum-square-error is observed, following the initial rapid reduction. Experience says that a certain amount of gradual reduction results in an improved neural network model, but too much can result in the overfitting phenomenon discussed in Chapter 4.

Figure 5.6 compares the neural network predictions and noise measurements for the training and check data sets. The standard deviations of the residuals are 2.4 and 3.5 respectively.

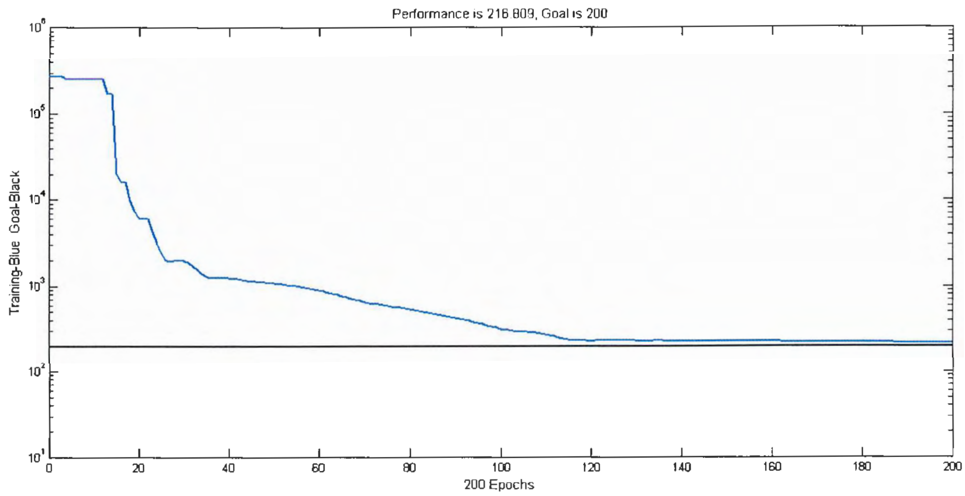


Figure 5.5 Neural network sum-square error vs training epoch record.

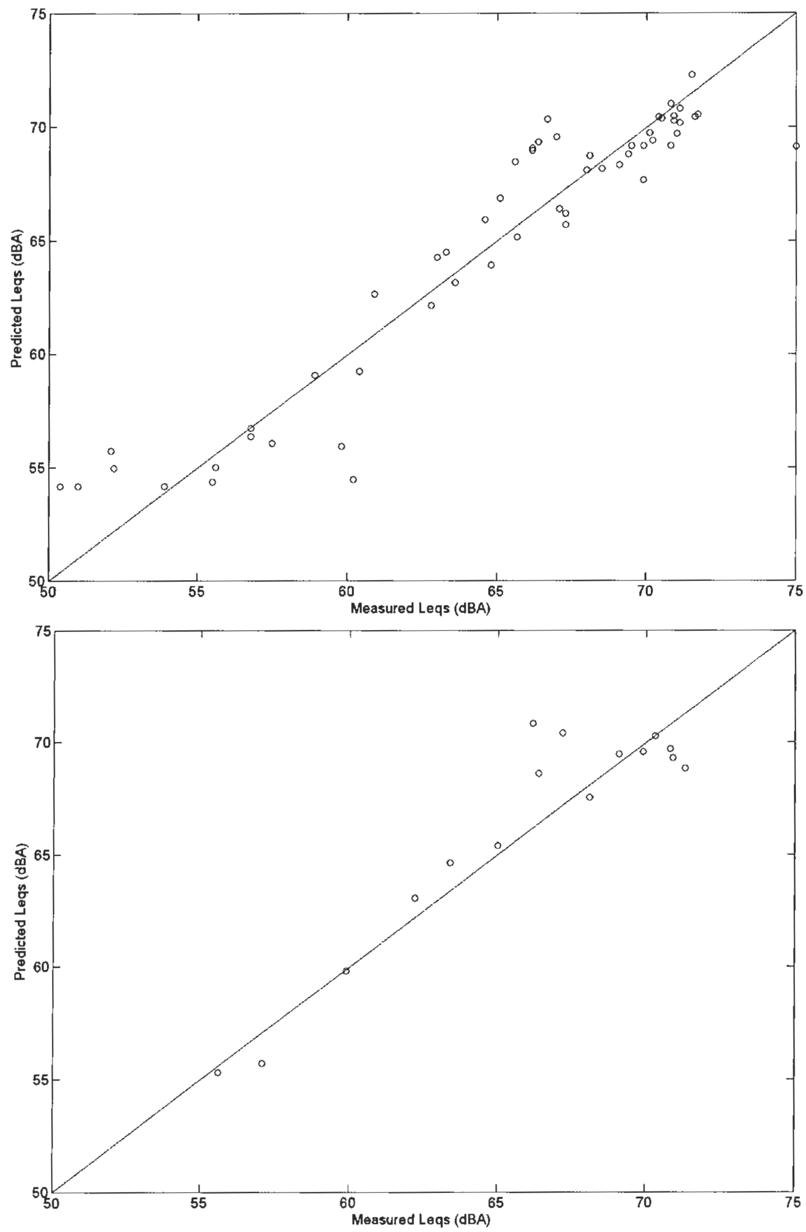


Figure 5.6 Neural network performance. Top: training data. Bottom: check data.

Figure 5.7 shows the variation of L_{eq} (1 h) noise levels with light vehicle and heavy vehicle counts per hour, as predicted by the neural network. The number of medium vehicles per hour did not vary much in the measurement program, and in the Figure 5.7 plots this input is kept constant at its mean value of 9 vehicles per hour.

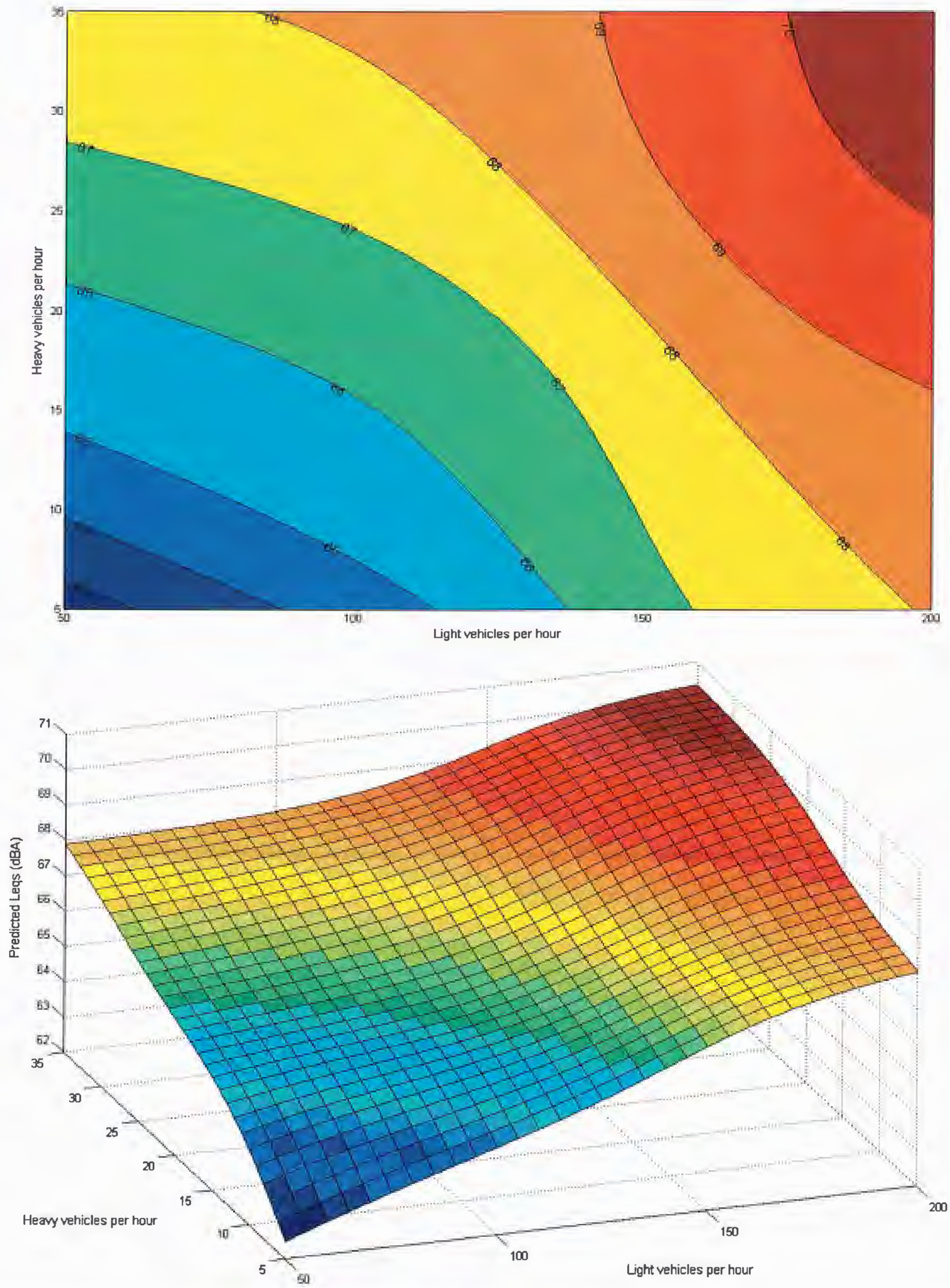


Figure 5.7 Contour and surface plots showing the variation of neural network predictions of L_{eq} (1 h) values (dBA) with light and heavy vehicle counts.

Figure 5.8 shows the variation of L_{eq} (1 h) noise levels with light vehicle and heavy vehicle counts per hour, as predicted by STAMSON.

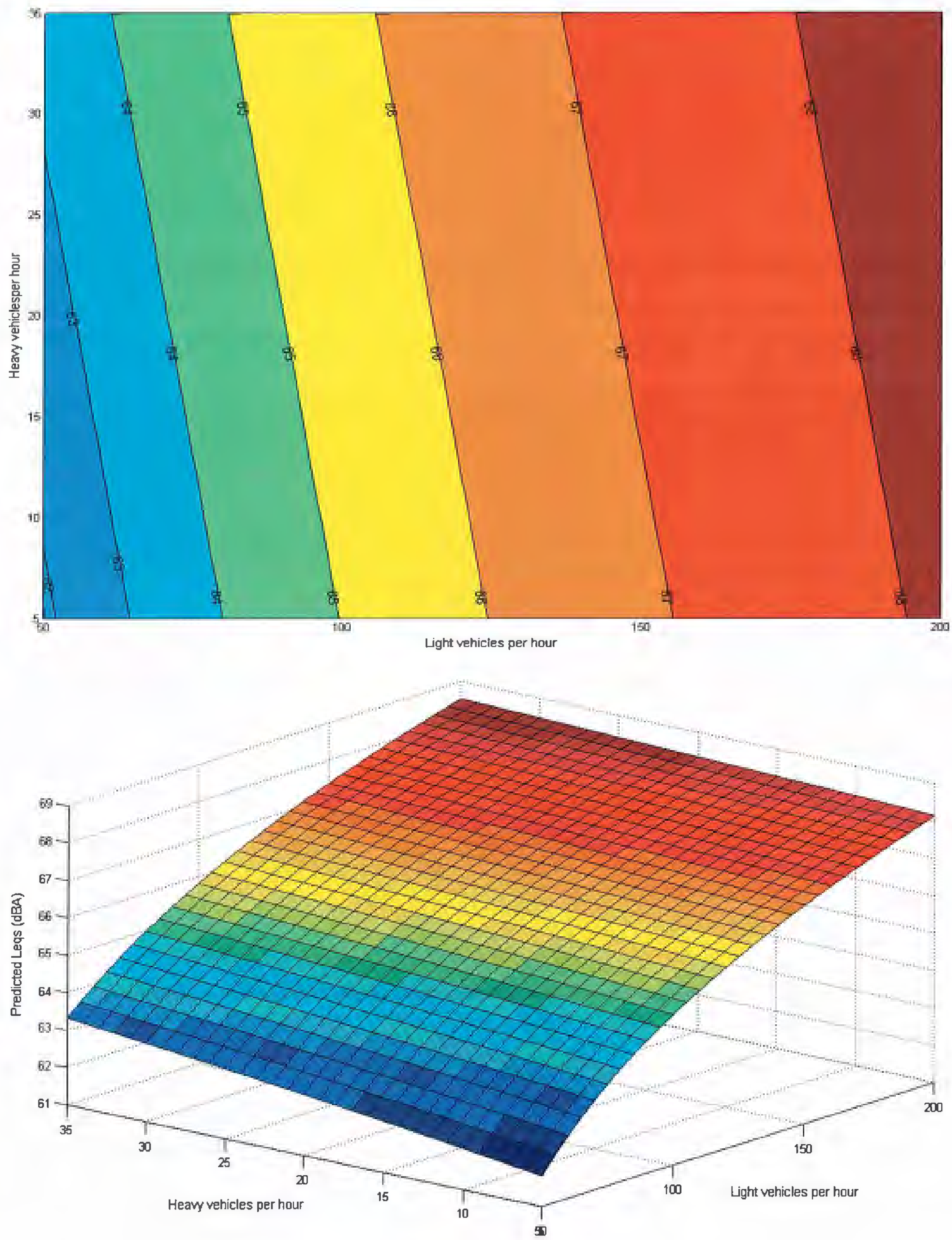


Figure 5.8 Contour and surface plots showing the variation of STAMSON predictions of L_{eq} (1 h) values (dBA) with light and heavy vehicle counts, for a speed of 70 km/h and a minimum road-receiver distance of 15 m.

The L_{eq} (1 h) plots in Figure 5.8 assume a posted speed limit of S = 70 km/h. The light, medium and heavy vehicle reference equivalent sound levels that STAMSON uses are given by Schroter & Chiu (1989) as:

$$(L_o)_{LV} = 38.1\log S - 2.4 \text{ dB}$$

$$(L_o)_{MV} = 33.9\log S + 16.4 \text{ dB} \qquad \text{Eqn 5.1}$$

$$(L_o)_{HV} = 24.6\log S + 38.5 \text{ dB}$$

From Chapter 3, the equivalent sound level, L, at a distance of $D_{ref} = 15$ m from the road for a given hourly traffic volume, V, with speed S = 70 km/h, is computed by logarithmically adding the three component reference equivalent sound levels, weighted by the percentage of vehicles in each class, $P_i = \{P_{LV}\ P_{MV}\ P_{HV}\}$, with the road gradient factor assumed to be unity, $K_g = 1$.

$$L(\text{dB}) = 10\log\sum_{i=1}^{3}\{K_g\, P_i\, 10^{(L_o)_i/10}\} + 10\log V - 10\log S + 10\log D_{ref} - 25 \qquad \text{Eqn 5.2}$$

Simplifying:

$$L(\text{dB}) = 10\log\{P_{LV}\ \alpha_{LV} + P_{MV}\alpha_{MV} + P_{HV}\alpha_{HV}\} + 10\log V - 31.69 \qquad \text{Eqn 5.3}$$

where $\alpha_{LV} = 10^{(L_o)_{LV}/10}$ $\alpha_{MV} = 10^{(L_o)_{MV}/10}$ $\alpha_{HV} = 10^{(L_o)_{HV}/10}$ Eqn 5.4

and $-10\log(70\text{ km/h}) + 10\log(15\text{ m}) - 25 = -31.69$ dB Eqn 5.5

Comparison of the neural network model and STAMSON L_{eq} (1 h) values in Figure 5.7 and Figure 5.8 respectively shows that the neural network model has successfully identified the basic relationship between traffic volume, percentage of light, medium and heavy vehicles, and the measured L_{eq} (1 h) values. The small differences between the neural network model L_{eq} (1 h) predictions and the STAMSON L_{eq} (1 h) predictions can largely be attributed to:

1) The influence of vehicle speeds on the measured L_{eq} (1 h) values, which the neural network knows nothing about. The STAMSON model is designed for use with Annual Average Daily Traffic values and the posted speed limit; and noise standards in Canada assume that there will be variations from the resulting mean Leq predictions.

2) The influence of different road-receiver distances at the three noise monitoring sites. Ideally sufficient data would be gathered at a single site at specific road-receiver distance to enable a neural network to be trained either for application to that site; or sufficient data would be gathered at different road-receiver distances to enable a neural network to be trained to take account of this parameter.

3) Neural network training data which does not quite cover the various combinations of the input variables.

Nevertheless, the neural network approach to modelling road traffic has performed as well as could be expected for this case study, with training data that were not ideal for the purpose.

One curious aspect of the neural network and STAMSON L_{eq} (1 h) predictions, is that the neural network L_{eq} (1 h) values in Figure 5.7 are comparable to the STAMSON L_{eq} (1 h) values in Figure 5.8 in some parts of the plots (i.e. for some combinations of light and heavy vehicles per hour). In other parts of the plots the STAMSON predictions are up to ~4 dBA lower than the neural network predictions.

A proper comparison between the two sets of values should add about 4.8 dBA to the STAMSON values, to account for the difference in road-receiver distances, using the standard correction (see Chapter 3):

$$10 \log_{10}\left(D_{ref}/D\right) \qquad \text{Eqn 5.6}$$

with D_{ref} = 15 m and $D \approx 5$ m.

This means that STAMSON and the neural network are in accord for some combinations of light and heavy vehicles per hour, but STAMSON is underpredicting the L_{eq} (1 h) values by about 4 dB for other traffic situations, which is a huge difference in noise modelling work. Better agreement between the two sets of predictions can be obtained by increasing the assumed speed limit from 70 km/h to 80 km/h in the STAMSON predictions, but this is not a change that reflects the actual situation: few vehicles would have been travelling at this speed, and hopefully none in the 60 km/h zones for the Ridgely and Romaine Creek sites.

The cause of this phenomenon is not known, but thought to be due to the predominance of certain kinds of vehicles in the traffic using the B17 road. It is probably not due to differences in the general vehicle fleet, since these data relate to the vehicle fleet of 1992/93.

Overall, however, it is clear that a neural network approach offers great potential for noise prediction modelling of site-specific situations such as the one presented in this case. It is unfortunate that the influence of site-specific factors such as terrain and road geometries preclude the application of a neural network trained for a given site to another site, and necessitate the gathering of site-specific neural network training and test data. However, other environmental assessment tasks such as air dispersion modelling work are also site specific in nature, and a site-specific noise prediction model can be implemented with effort and technical knowledge comparable to that needed to carry out a dispersion modelling exercise, and it can be carried out with off-the-shelf software (e.g. Matlab). Given that a neural network modelling approach offers better performance than present traffic noise prediction models for these site-specific applications, there is no reason why regulatory authorities should not start to ask for noise impact studies to be based on this approach.

6.0 MODELLING STRATEGY FOR COMPLEX SITUATIONS

6.1 Overview

As discussed in Chapter 3, present road traffic noise prediction models, such as STAMSON or TNOISE, can only handle two-dimensional (2-D) situations as a superposition of component 1-D situations, for example by modelling the effect of a barrier as the superposition of noise from traffic on those sections of road that lie behind the barrier, and those sections that are not shielded by the barrier. This strategy works well to an extent, but it cannot address many situations of practical interest, whose road, terrain, or building geometries preclude a decomposition into 1-D component situations

A neural network modelling approach has the potential to handle these more complex situations, because neural networks have a proven ability to discern patterns in 2-D data. The use of neural networks to detect patterns in 2-D data has been used successfully in applications such as face recognition in images (e.g. Omidvar & Dayhoff, 1998), and in the mining industry. Schrader & Balch (2006) note that neural networks can carry out analysis of patterns in gridded map data, essentially interpreting them in the same way an experienced geologist interprets a feature map. This kind of application is very close to the present problem, and motivates consideration of development of a traffic noise prediction neural network that relates to a grid of input data and output predictions.

6.2. Modelling Strategy

We assume that associating grid coordinates with input data is indeed the key to using a neural network approach to predicting road traffic noise levels in 2-D situations. However, the grid coordinates themselves are not needed for modelling patterns in a standardised grid, because every grid point has associated input data, and the grid point data is always presented to the neural network in the same order. For example, analyzing patterns in images that are all the same size (N rows x M columns) simply requires training a neural network that accepts a set of N x M colour intensity values.

This is clearly the easiest approach to developing a grid-based neural network, and input data such as digital terrain elevations and building locations can be easily referred to a grid (in the case of the barrier a simple 1 = building and 0 = no building scheme would suffice). However, noise measurements are made only at specific points within a grid, and a data gridding pre-processor routine is needed to produce the required grid of target measured noise values.

Beyond consideration of grids, there are two ways to apply a 2-D road traffic noise prediction modelling approach based on the use of one or more neural networks. The first approach is to develop a site-specific model, in which case the strategy would be to train a single neural network defined over a suitable grid, using noise measurements made at various locations across the grid for a range of traffic conditions sufficient to provide input, validation, and check data.

Essentially, this is a model that interpolates several 1-D neural network models of the kind demonstrated in Chapter 5. In other words, the data gathered at each point in the grid could be used to develop a 1-D model such as that presented in Chapter 5. The 2-D model simply requires a neural network to produce the 1-D model predictions at each of the grid points at which noise measurements were made, and interpolate between the 1-D predictions at other grid points. This exercise is not very different to that presented in Chapter 5, and would have only incremental research merit.

The second 2-D road traffic noise prediction modelling approach is to produce a *general* modelling capability, which is a far more challenging exercise. Indeed, this is the holy grail of road traffic noise modelling. How best to approach this work? Well, artificial intelligence tools are based on biomimicry principles, and biomimicry can also guide the strategies to apply these tools. It is common wisdom that people solve complex problems by breaking them into component tasks to the extent possible, which accords with the modelling strategy of STAMSON and TNOISE in quasi 2-D situations.

Applying this strategy, it was decided to:

1) Develop a neural network to predict the 2-D dependence of L_{eq} values on traffic speed across a grid of flat terrain, for each vehicle class. These three baseline grids are the 2-D equivalent of the three reference L_{eq} values for present road traffic noise models.

2) Combine the three baseline L_{eq} grids using the mathematics of logarithmic quantities, in the same manner as is done by STAMSON and TNOISE to produce an overall L_{eq} reference grid that reflects the actual traffic count and percentage breakdown of the three vehicle classes. This is the single baseline L_{eq} grid for a given traffic noise prediction exercise.

3) Develop and use a suite of additional neural networks to modify the baseline L_{eq} reference grid by various adjustments as appropriate, which again mimics the strategy used by present traffic noise prediction models such as STAMSON.

6.3 Neural Network Architecture for the Baseline Grid

A 100 m x 150 m noise prediction grid, shown in Figure 6.1, was defined for the purposes of the present research. The 100 m dimension is measured away from the road, and the 150 m dimension is measured along the road. The grid squares are each 10 m x 10 m.

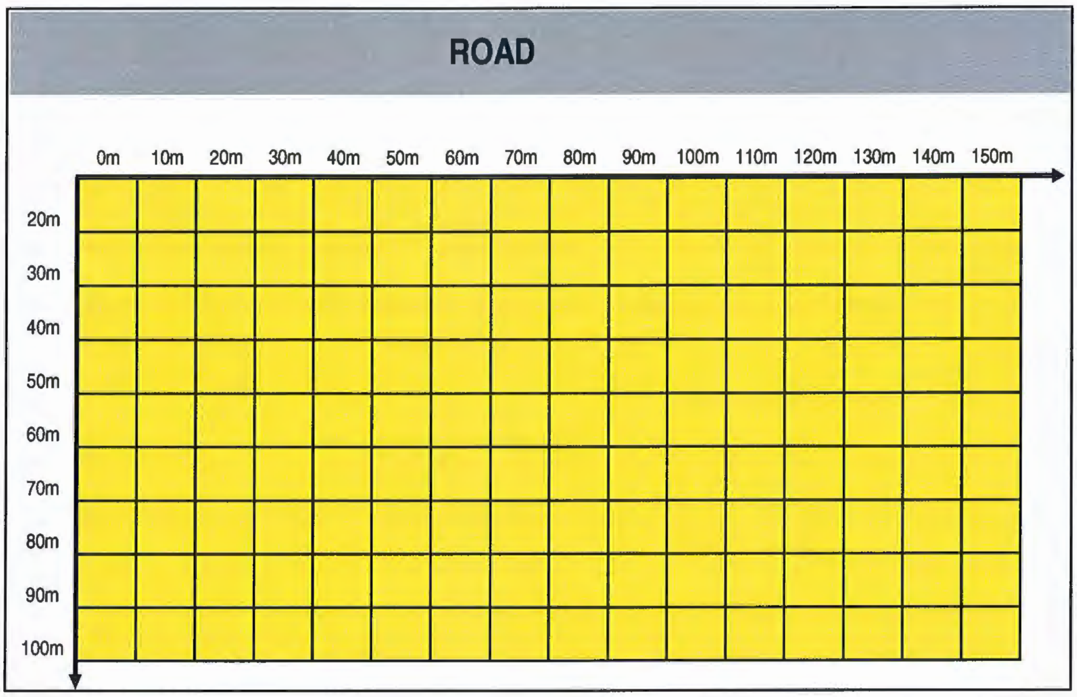


Figure 6.1 Noise prediction grid.

The neural network is thus required to produce 9 x 16 = 144 output L_{eq} values (in dBA), across the grid. These L_{eq} values are for a specific speed limit, assuming baseline traffic flows and other conditions. Therefore the neural network must be trained using several sets of such predictions, each for a different speed limit.

STAMSON was used to produce sets of input data for the heavy vehicle baseline L_{eq} grid. The baseline conditions were 50 heavy vehicles per hour, a receiver height of 1.5 m above the ground, and flat absorptive terrain. To simplify matters, the training and check data are also provided at each grid point, although if a baseline grid were being produced from a limited number of real measurements instead of synthetic data provided by STAMSON, then the grid of input L_{eq} values would need to be produced by interpolating the measurements to the 144 grid based values.

Figure 6.2 shows L_{eq} input values for a posted speed of 80 km/h. The grid coordinate system refers to the middle of each cell. For example, the L_{eq} = 62.6 dBA value in the top left grid square relates to a position 20 m from the road side, and on the edge (0 m) of the grid.

ROAD

	0m	10m	20m	30m	40m	50m	60m	70m	80m	90m	100m	110m	120m	130m	140m	150m
20m	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6	62.6
30m	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7	59.7
40m	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6	57.6
50m	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0
60m	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7	54.7
70m	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6
80m	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6	52.6
90m	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8	51.8
100m	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0	51.0

Figure 6.2 **Neural network input L_{eq} values (dBA) for 50 heavy vehicles per hour, and a posted speed limit of 80 km/h.**

After some experimentation, a neural network with satisfactory performance was achieved by a two layer feed-forward architecture consisting of 25 neurons in the input layer of neurons, with tangent-sigmoidal transfer functions; and 144 neurons in the output layer of neurons, with pure line transfer functions.

This neural network, trained on four sets of input data corresponding to speed limits of 40, 60, 80, and 100 km/h, was able to generalise satisfactorily to predict the variation of L_{eq} values with distance for other speed limits. Figure 6.3 compares the neural network L_{eq} predictions for a speed of 70 km/h, to the STAMSON predictions. The baseline grid assumes flat terrain, and the road is parallel to the grid and is of "infinite" length, so the L_{eq} noise level contours lie parallel to the road. This is the grid-based equivalent of the 1-D neural network training exercise described in Chapter 4.

Figure 6.3 shows that there is fairly good agreement between the L_{eq} values predicted by the neural network, and the target L_{eq} values produced as check data by STAMSON. The predicted values of 53 dBA, 57 dBA and 60 dBA vary slightly (typically ±0.5 dBA) from the model calculations for the distance from the road but are consistent with training the neural network with L_{eq} grids corresponding to only four speeds.

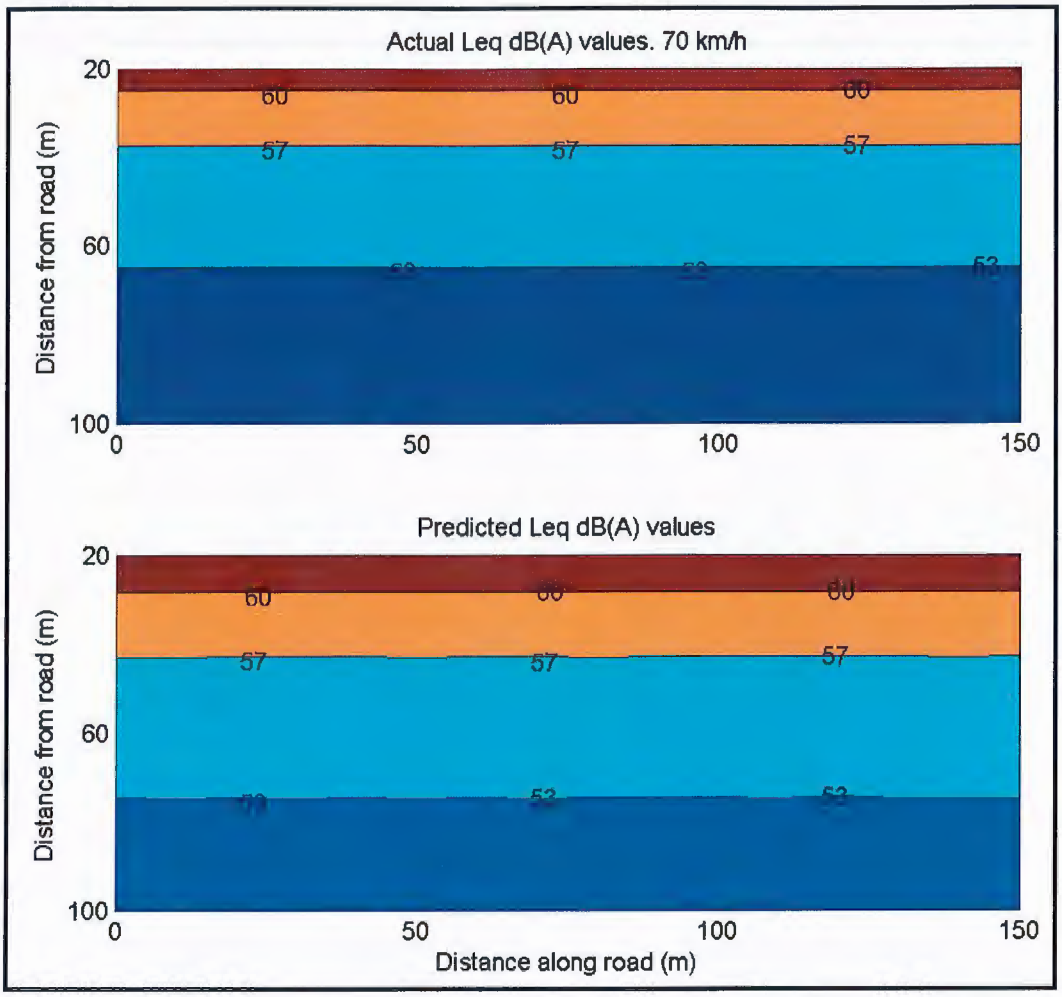


Figure 6.3 **L_{eq} values for 70 km/h, and baseline heavy vehicle conditions. Top: "Actual" L_{eq} values provided by the STAMSON model. Bottom: L_{eq} values predicted by the neural network.**

Similar baseline L_{eq} grids can be produced for the other two vehicle classes (light and medium vehicles), and together these are the equivalent of the three speed-dependent reference L_{eq} values defined by models such as STAMSON and TNOISE for 1-D situations.

This completes the first stage of the neural network model development strategy set out in Section 6.2.

The second stage of the strategy, to produce an overall baseline L_{eq} grid, is straightforward. Chapter 4 explains the adjustment to the reference equivalent sound level to account for the actual traffic count, V, being different to the reference traffic count, which in this case is V_{ref} = 50 vehicles per hour. Chapter 4 also explains the adjustment that takes into account the relative contribution of the three baseline grids to the overall according to the decimal percentage of vehicles in each class, $P_i = \{P_{LV}\ \ P_{MV}\ \ P_{HV}\}$. This calculation is applied to the L_{eq} values calculated at every grid point, and the result is the final baseline L_{eq} grid for a given situation.

6.4 Barrier Effect Adjustment

The third stage of the model development strategy is to apply a set of adjustments to the overall baseline L_{eq} grid to account for departures from the baseline conditions due to influences such as terrain, barriers, and buildings.

To demonstrate the proposed methodology, this research examines the neural network modelling effort needed to take into account the effect of a straight barrier located parallel to the road, within the 100 m x 150 m grid. Figure 6.4 shows a 70m long barrier located 45 m from the road side, denoted by the heavy black line, and the associated pattern of L_{eq} (dBA) adjustments to the baseline L_{eq} values due to the barrier. As discussed in Section 6.3, the adjustment values relate to the distances from the road side of 20m, 30m, 40m and so on, while the horizontal grid lines separating the values are located at distances from the road side of 25 m, 35 m, 45 m and so on. The road is parallel to the top side of the grid, and for the sake of clarity only a portion of the 100 m x 150 m grid is shown.

	0m	10m	20m	30m	40m	50m	60m	70m	80m
20m	0	0	0	0	0	0	0	0	0
30m	0	0	1.0	1.0	1.0	1.0	1.0	0	0
40m	0	2.0	2.5	2.5	2.5	2.5	2.5	2.0	0
50m	0	-7.0	-9.0	-11.0	-11.0	-11.0	-9.0	-7.0	0
60m	0	0	-7.0	-9.0	-11.0	-9.0	-7.0	0	0
70m	0	0	0	-7.0	-9.0	-7.0	0	0	0
80m	0	0	0	0	-7.0	0	0	0	0
90m	0	0	0	0	0	0	0	0	0

Figure 6.4 L_{eq} (dBA) adjustments for a 70 m long barrier.

In Figure 6.4, the L_{eq} adjustments due to the barrier effect are only synthetic values. They are simply intended to define a typical pattern of noise level adjustments in front of the barrier, and behind the barrier in its shadow zone. They do not define adjustments that are acoustically correct for a barrier of a specific material and height.

Reflection of noise from the barrier face increases noise levels on the road side of the barrier, while noise levels are decreased in the barrier's shadow zone. The 2.0 dB L_{eq} increase in the left most grid square on the road side of the barrier relates to a position 40 m from the road edge, 5 m in front of the barrier, and 10 m from the left edge of the grid. The 7.0 dB L_{eq} decrease in the left most grid square on the shadow side of the barrier relates to a position 50 m from the road edge, 5 m behind the barrier, and 10 m from the left edge of the grid.

The L_{eq} adjustments of 2.0 dB and 2.5 dB in front of the barrier, dropping to a 1.0 dB adjustment 10 m in front of the barrier, are synthetic but realistic, since a perfectly reflective barrier will produce a 3 dB increase (i.e. a doubling) in sound levels. Behind the barrier, a triangular pattern of L_{eq} adjustments is specified. The triangular pattern is only a crude approximation to the actual changes in a noise field due to the presence of a barrier (e.g. Menge et al., 1998), but simplifies the training of a neural network in this research exercise.

The neural network is trained on a number of training data sets, each of which consists of an input grid of values and a target grid of values. Each input data set consists of 9 x 16 = 144 values of either one or zero. For the 70 m long barrier in this demonstration , seven input values are set to one, denoting the location of the 70 m barrier, and the remaining 137 values are set to zero. Each target data set consists of the 9 x 16 L_{eq} adjustment values for the given barrier position, with Figure 6.4 showing a subset of values for the barrier position shown (only a portion of the 100 m x 150 m grid is shown).

The neural network is trained by requiring it to produce the correct pattern of L_{eq} adjustments for a given barrier location, for each training data set. As usual, a key question is how many input data sets of barrier locations and associated target data sets of L_{eq} adjustments are needed to properly train the neural network. The test is whether the neural network can generalise to correctly predict the L_{eq} adjustments for barrier locations that were not part of the training data.

The initial approach to this task was to train the neural network using data sets corresponding to randomly positioned barriers, but it was found to be impossible to train a neural network that could successfully generalise to predict L_{eq} patterns for a barrier at a location in the grid that was not part of the training data set.

The problem with this neural network training approach emerges from consideration of the minimum input data requirements. The key requirement for a successful training exercise is to ensure that all the 144 input values take on both possible values, one and zero, at least once, and preferably more than once. The reason for this is that a neural network quickly – and understandably – learns to ignore inputs that are either constant, or which do not appear to be related to the required output. Mathematically, "ignore" means assigning very low weights to these inputs, which minimises their influence on the sum of the weighted inputs that is presented to a given neuron's transfer function.

There are ten possible locations for a 70 m long barrier on each of the nine rows in the grid, giving a total of 90 possible barrier locations. The set of barrier locations used to train the neural network must thus contain at least three barriers on each row (i.e. 3 x 9 = 27 training data sets), or some inputs will always be zero.

However, unless the training data contains at least four barriers on each row, many input values are only set to one on a single occasion. This is not sufficient for a neural network to properly recognise how the pattern of ones and zeros in the input data is related to the required pattern of L_{eq} adjustments.

Experimentation found that a neural network with the same architecture as that described in Section 6.3 for the baseline grid predictions, but with 120-150 neurons in its input layer, could be trained to recognise the barrier effect, with the training data set consisting of a minimum of 35 barriers, each 70 m long.

Figure 6.5 shows the L_{eq} adjustment predictions of the neural network for three 70 m barrier locations that were not part of the training data. The contour values are –10, -9, -8, -6, -5, +1, and +2 dB. Figure 6.5 shows that the neural network has successfully been able to generalise its ability to predict the pattern of L_{eq} adjustments for a barrier to barriers that were not part of the training data set. These adjustments are logarithmically added to the baseline L_{eq} predictions at each point in the grid.

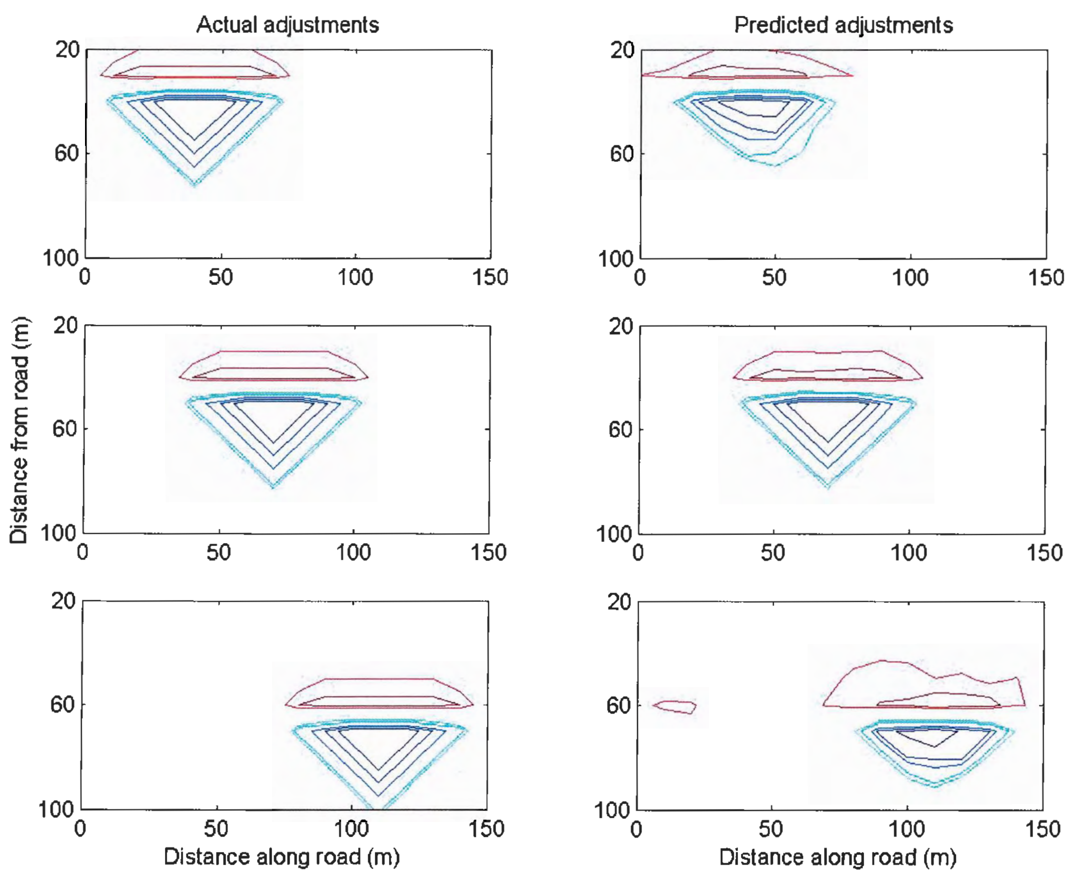


Figure 6.5 Comparison of L_{eq} adjustments due to a barrier. Left: Nominal "actual" L_{eq} adjustments. Right: L_{eq} adjustments predicted by the neural network.

6.5 Discussion

As noted in the introduction to this chapter, a *site-specific application* of a grid-based neural network is essentially an extension of the 1-D modelling approach, and is not examined here. Nevertheless, it must be emphasised that a site-specific 2-D noise prediction model has clear potential to be an extremely useful tool for noise impact assessment, and goes well beyond the ability of present noise traffic prediction models.

This chapter has proposed a methodology for developing a *general application* road traffic noise prediction model using grid- based neural networks. The strategy is very similar to that used by present noise traffic prediction models, and this chapter has examined the architecture of neural networks able to produce a baseline (reference) L_{eq} grid and a grid typical L_{eq} adjustments.

The main question remaining is how best to translate this research into a commercial product. In the case of the general 1-D model and site-specific 2-D model, the existing Matlab software platform and its neural network toolbox are sufficient to produce a suitable commercial product. In the case of the general 2-D model, the aim of a prototype software system would be to properly handle a limited number of adjustments, such as variable terrain, simple barriers, the presence of one or two buildings. A third-party Matlab toolbox of routines designed to assist an acoustician implement a model would be useful, because the nature of neural networks is such that a simple push-button noise prediction model is not likely to be possible, and certainly not as a prototype.

The more likely scenario is that a user establishes a basic 2-D model for a given situation by defining the location of barriers and buildings, and providing a digital terrain elevation file. The neural networks that produce baseline L_{eq} grids and L_{eq} adjustments should be pre-trained, but additional training will likely be needed to fine-tune the L_{eq} predictions for the situation. This is exactly the same as the commercially available neural networks that are used for speech or character (i.e. writing) recognition. Both the speech and the character recognition neural networks are pre-trained to recognise clear speech and "perfect" characters, but then need additional training to perform well on the particular accent and writing style of the person using the neural networks.

A question remains regarding the ability of the L_{eq} adjustment neural networks to generalise to new situations. The task of producing neural networks that perform well in this regard is simplified by three factors. First, Matlab can read Excel files, and this greatly facilitates preparation of neural network training data sets.

Second, a basic set of barrier L_{eq} adjustments for a barrier at one location in a grid will also serve for L_{eq} adjustments associated with a barrier elsewhere in the grid, as was demonstrated by the case study presented in this chapter. The barrier L_{eq} adjustments in the case study were assumed to not be functions of distance from the road, so the 35 input data sets used to train the neural network could be generated from a single set of L_{eq} adjustments. But even if the adjustments were functions of distance (and, of course, they are), all the input data sets for a barrier at a given distance from the road could be generated from a single set of L_{eq} adjustments. Similar comments apply to L_{eq} adjustments for buildings within the grid.

Third, acoustic theory can help to prepare suitable grids of L_{eq} adjustments from a limited number of field measurements. For example, the way in which sound refracts and diffracts in response to objects in the propagation path is well understood, so theory can be used to interpolate and/or extrapolate from a limited number of measurements in the vicinity of a barrier or a buildings, to produce a full training grid of adjustments.

7.0 CONCLUSIONS AND FUTURE WORK

7.1 Research Overview

Motivation

After nearly 50 years working in the electricity generation industry, in government, and as a consultant, I began a Masters degree at the University of Tasmania to, in a sense, complete my life work as a professional in the field of acoustics. The field of acoustics has been a main stay for me over the years, and I have had a great deal of experience in the problem of noise emissions from numerous sources.

This research has been motivated by the fact that road traffic noise prediction models have not improved significantly since their development in the 1970s and 1980s, although road traffic noise nuisance is a significant and growing issue in Australia and elsewhere. The models are not able to credibly address many practical situations, and yet assessment of noise impact from road traffic is an ongoing issue, and occupied much of my time while working with the Tasmanian State government.

The present situation

Chapter 2 reviews the nature of road traffic noise, its measurement, and interpretation of noise levels in terms of noise nuisance. Although noise nuisance is a complex subject, there is little doubt that almost half the Australian population is exposed to at least some degree of noise nuisance, which makes it almost incredible that noise impact studies are not routinely required to support developments that might be impacted by road traffic noise, as is the case in countries such as Canada. It also highlights how serious is the problem of the lack of good road noise prediction models.

Chapter 3 examines the principal noise propagation influences that need to be described by road traffic noise prediction models, notably geometric spreading and ground attenuation, which are accounted for by a simple "distance adjustment"; and simple elevation changes and barriers, which are accounted for by semi-empirical adjustments that are typically hard-coded into models. Other noise propagation factors, such as atmospheric absorption and refraction, tend to be important on distance scales that are greater than the ~100 m or so that is usually the focus of interest in assessing road traffic noise impact.

Two typical examples of present road traffic noise prediction models are examined, namely the Canadian model STAMSON and the Australian model TNOISE. These models were based on earlier work in the U.S. and the U.K respectively, and are to a large extent pattern recognition tools. They compute basic noise levels for light, medium and heavy vehicles at a reference distance from the road based only on traffic speed, for baseline vehicle counts per hour, logarithmically add these quantities with consideration of actual speed and traffic composition, and apply semi-empirical adjustments to make noise level predictions further from the road, with consideration of barriers and other effects.

These models perform satisfactorily for very simple situations, examples of which are given in Chapter 3, but accurate noise prediction in more complex situations is beyond their ability. They can sometimes handle 2-dimension aspects of a situation as a logarithmic summation of 1-dimension components, an example being the assessment of traffic noise from a road whose line of sight from a received is partly blocked by an acoustic barrier or building. The 1-dimension components of this situation are the portion(s) of road that have line of sight to the received, and the portion(s) of road whose line of sight is blocked by the barrier. However, the number of adjustments necessary to handle more complex situations involving variable terrain, multiple building and/or barriers in a precludes using the approach used by present models to a next generation of model that is able to handle complex situations.

An example of a model that is able to consider such complexity, at least to an extent, is examined. However, the Environmental Noise Model is not well suited to predicting noise from line sources such as a road, and has not found much application outside of point source noise assessment work.

A neural network approach

Neural networks are artificial intelligence pattern recognition tools that have proven their power and usefulness in a variety of applications in recent years, and this thesis examines the hypothesis that a neural network approach to predicting road traffic noise offers a way to move forward in noise impact assessment.

Chapter 4 explains basic neural network theory, and determines that a two-layer feed-forward architecture can mimic present road traffic noise prediction models, with tangent-sigmoidal transfer functions specified for the input layer of 20-30 neurons, and a linear transfer function specified for the single output neuron. A priori rescaling of input values to roughly match the requirements of the transfer function facilitates the neural network training using a backpropagation algorithm with momentum and adaptive learning. Ways of avoiding the problem of overfitting are also discussed.

The chapter presents an example in which a neural network is trained to recognise the way in which equivalent sound levels (L_{eq} values) vary with traffic speed and distance from the road. This is a liner problem in log space, but the example considers ordinary values to illustrate how easily a neural network can determine non-linear patterns.

The Hampshire case study

A case study based on a 1993 noise impact assessment project for the Hampshire wood chip mill in northern Tasmania is presented. It demonstrates that a neural network can easily be trained from fairly limited field data to satisfactorily predict road traffic noise in site-specific situations. The 1993 project was to assess noise impact from heavy vehicle traffic on rural roads, and although the proposed wood chip mill was a major development for Tasmania, models such as STAMSON or TNOISE were not used for several reasons, notably because the receivers were too close to the road, and the heavy vehicle traffic was predominantly one type of vehicle, instead of the mix of vehicles assumed by the models.

The Hampshire project's field noise measurement program was not, of course, designed to gather data to train a neural network, but nevertheless combining data recorded at three similar stations provided a data set that proved acceptable for demonstration purposes. This case study highlights the fact that a neural network approach offers great potential for noise prediction modelling of site-specific situations that is significantly better than present traffic noise prediction models.

Strategy for modelling complex situations

The development of a grid-based neural network noise prediction model for a site-specific 2-dimensional situation is quite straightforward, only requires a single neural network, and has clear potential to be an extremely useful tool for noise impact assessment, and goes well beyond the ability of present noise traffic prediction models.

However, Chapter 6 of this thesis proposes a strategy for developing a *general application* road traffic noise prediction model using grid- based neural networks. Grid-based neural networks are not new, having found applications to date in applications such as recognising patterns in map-based geological data, and character recognition systems. The key to using such neural networks for road traffic noise prediction is to appreciate the value of using a staged strategy similar to that used by present noise traffic prediction models. The chapter outlines the proposed strategy, and examines the architecture of neural networks able to produce a baseline (reference) L_{eq} grid and typical L_{eq} adjustments to the grid of baseline values. Examples of both grids are give, the first for a heavy vehicle reference grid and the second for a barrier adjustment.

7.2 Future Work

This thesis has demonstrated that a road traffic noise prediction model using a neural network can not only mimic present noise prediction models, but it can out-perform these models in some site-specific situations for which the present models are not well suited, for various reasons.

It is therefore recommended that demonstration projects be initiated by road traffic authorities to build confidence in such an approach. A key to this will be to establish new, more extensive 2-D sets of site measurements against which to test the performance of site-specific neural network models. Artificial intelligence methods are now taught in undergraduate engineering degree programs, and the knowledge and skill needed to implement such an approach is no more than is necessary to implement an *Ausplume* air emission dispersion modelling exercise.

The second recommendation for follow-on work is to develop a Matlab toolbox that is able to provide road traffic noise predictions for 2-dimensional situations using grid-based neural networks, following the strategy proposed in Chapter 6. There are several aspects of such a modelling effort that will need to be better understood, but it is possible that the reward will be having a road traffic noise prediction capability able to address variable terrain, buildings, barriers, and so forth. The commercial potential of such a tool, and its regulatory benefits, if this research direction proves sound, are obvious.

The present road traffic noise prediction models are underpinned by a great amount of empirical work carried out by many dedicated acousticians in the 1960s to 1980s. They represented a major step forward in our understanding of road traffic noise, and our ability to predict it.

As a final thought, it is very satisfying at the end of my career in acoustics to be able to suggest a way to provide the next generation of acousticians with next generation tools for road traffic noise prediction.

8.0 REFERENCES

ABS 2006. *Sales of New Motor Vehicles, Australia,* Australian Bureau of Statistics, publication 9314.0, May 2006.

Avşar Y., Saral A., Gönüllü M. T., Arslankaya E., & Kurt U. 2004. *Neural Network Modelling of Outdoor Noise Levels in a Pilot Area*, Turkish Journal of Engineering and Environmental Sciences, 28, pp149:155, 2004

Barry, T.M., & Reagan, J.A. 1978. *FHWA Highway Traffic Noise Prediction Model.* Report No. FHWA-RD-77-108. Federal Highway Administration, Washington, DC, Dec 1978.

Bass, H.E., Sutherland, L.C., Zuckerwar, A.J., Blackstock, D.T. & Hester, D.M., 1995. *Atmospheric Absorption of Sound: Further Developments,* Journal of the Acoustical Society of America, Vol. 97 (1), January 1995.

Bishop, C.M. 1995. *Neural Networks for Pattern Recognition.* Clarendon Press, Oxford.

Bowers, J.F., Bjorkland, J.R. & Cheney, C.S. 1979, *Industrial Source Complex (ISC) Dispersion Model User's Guide.* Report EPA-450/4-79-030. U.S. Environment Protection Agency, 1979.

Cammarata, G., Cavalieri, S. Fichera, A., & Marletta, L. 1993. *Noise Prediction in Urban Traffic by a Neural Approach.* In *New Trends in Neural Computation*, Proceedings of the International Workshop on Artificial Neural Networks, pp611-619, Spain, June 1993, Springer.

Carter, S.J.B., van Emmerik, A.J., Freeman, P.R., & Parker, L. 2000. *Multi-Lane Traffic Surveys Using Pattern Recognition.* In Proceedings of the International Conference on Artificial Intelligence in Science and Technology (AISAT), University of Tasmania, Hobart, Australia, December 2000, pp231-236.

Davis, H. & Stevens, S.S., 1983. *Hearing- Its Psychology and Physiology.* Originally published in 1938; Reprinted in 1983 by the Acoustical Society of America.

Demuth, H., Beale, M. & Hagan, M., 2006, *Neural Network Toolbox 5 Users Guide*, The MathWorks Inc,, Natick, MA, USA.

Doolan B.L. & Carter S.J.B, 2005. *Road Traffic Noise Prediction: An Artificial Intelligence Approach*, Australian Acoustical Society Annual Conference *Acoustics 2005 –Acoustics in a Changing Environment*. Busselton, 2005.

Doolan, B.L. 2004. *Noise Measurement Procedures Manual.* Document prepared under contract to the Tasmanian Department of Primary Industries, Water and Environment, July 2004.

E&TS 1993. *APPM Hampshire Satellite Mill: Development Proposal and Environmental Management Plan,* Environmental & Technical Services Report to Tasmanian State Government Department of Environment and Land Management, Hobart, 31 May 1993.

Fujiwara, K., Ando, Y. & Maekawa, Z. 1973. *Attenuation of a spherical sound wave diffracted by a thick plate*. Acoustica 28, 341-347, 1973.

Fujiwara, K., Ando, Y., & Maekawa, Z. 1977a. *Noise control by barriers – part 1: Noise reduction by a thick barrier*, Applied Acoustics, 10 (2), 147-159, 1977.

Fujiwara, K., Ando, Y., & Maekawa, Z. 1977b. *Noise control by barriers – part 2: Noise reduction by a thick barrier*, Applied Acoustics, 10 (3), 167-179, 1977.

Harris C. M., 1979. *Handbook of Noise Control*, 2nd Edition,McGraw-Hill, 1979.

Holmes Air Sciences 1997. *Guidelines for assessing noise under meteorological conditions leading to enhanced noise levels.* Report to the NSW EPA, 1997.

Job, R.F.S. 1996. *The influence of subjective reactions to noise on health effects of the noise.* Environment International, 22, 93-104, 1996.

Larsson C. 2000. *Weather effects on outdoor noise propagation*, International Journal of Acoustics and Vibration, Vol. 5, No.1, 2000.

Lorimer, G. 1986. *The Ausplume Gaussian Plume Dispersion Model.* Victoria Environment Protection Authority Publication 264.

Maekawa, Z., 1968. *Noise Reduction by Screens*, Applied Acoustics 1, 157-173, 1968.

Magrab E. B., 1975. *Environmental Noise Control*, John Wiley 1975.

El Mallawany, A. I., Abdallah, M. I., & Abd El Gawad, M. 1999. *Modeling of traffic noise pollution with neural networks.* Journal of the Acoustical Society of America, 105, 2, p1335 February 1999.

Manning, C.J., 1981. *The propagation of noise from petroleum and petroleum complexes to neighbouring communities,* CONCAWE Report 4/81, May 1981, Den Haag NL.

Marion, J.B & Heald, M.A. 1980. *Classical Electromagnetic Radiation, 2nd Ed.* Academic Press.

Menge, Christopher W., Christopher J. Rossano, Grant S. Anderson, Christopher J. Bajdek. FHWA Traffic Noise Model,® Version 1.0: Technical Manual. Report No. FHWA-PD-96-010 and DOT-VNTSC-FHWA-98-2. Cambridge, MA: John A. Volpe National Transportation Systems Center, Acoustics Facility, February 1998.

MOE, 1997. *Noise Assessment Criteria in Land Use Planning,* Ministry of the Environment, Ontario Publication LU-131, October 1997.

NTC, 2001. *A Review Of The Noise Related Australian Design Rules And Engine Brake Noise.* Report by W. Harry Close of Apelbaum Consulting Group to the National Transport Commission, April 2001.

Negnevitski, M., 2003, *Artificial Intelligence,* Addison-Wesley, 2003

Makarewicz, R. 1997. *Influence of ground effect and refraction on road traffic noise,* Applied Acoustics, 1997, Vol. 52, No. 2, pp125-137.

NSW EPA, 1999. *Environmental Criteria for Road Traffic Noise*, New South Wales Environment Protection Authority, 1999.

Omidvar, O. & Dayhoff, J.E. (1998). Eds. *IEEE Transactions on Neural Networks, Special Issue on Neural Networks and Pattern Recognition.* Elsevier 1998.

Piercy, J.E., Embleton, T.F.W. & Sutherland, L.C. 1977. *Review of noise propagation in the atmosphere,* Journal of the Acoustical Society of America, Vol. 61 (6), June 1977.

Queensland EPA 2000. *State Interest Planning Policy for Noise Management in Planning Schemes,* Environment Protection Agency, Queensland, June 2000.

Schrader, S.M. & Balch, R.S., 2006. *Automated Analysis of Gridded Geologic Map Data.* Oral presentation at AAPG Annual Convention, Houston, Texas, April 9-12, 2000, available from http://www.searchanddiscovery.net/documents/2006/06049schrader/index.htm.

Schroter, V. & Chiu C. 1989. *ORNAMENT – Ontario Road Noise Analysis Method for Environment and Transportation* Ministry of Environment, Ontario, October 1989.

SoE 2001. *Australia: State of Environment 2001.* Report to the Commonwealth Government by the State of the Environment Advisory Council, CSIRO Publishing.

Sutherland, L.C. 2000. *Overview of Outdoor Sound Propagation,* 29th International Congress and Exhibition on Noise Control Engineering, 27 -30 August 2000, Nice, France.

Tasmania DPIWE 2004. *Environmental Management and Pollution Control (Miscelleneous Noise) Regulations 2004*, State Regulations 2004, No 50. Prepared by the Department of Primary Industries, Water and Environment.

Tonin, R. 1986, *Environmental Noise Model*, RTA Technology Pty Ltd, Sydney, 1986.

UK DoT, 1988. *Calculation of Road Traffic Noise*, U.K. Department of Transport, Welsh Office, H.M.S.O. 1988.

Victoria EPA 2002. *Road Traffic Noise Strategy Background Paper,* Environment Protection Authority, Victoria, Publication 845, May 2002.

Victoria EPA 2003. *Environment Protection (Vehicle Emissions) Regulations,* Environment Protection Authority, Victoria, 2003.

WA DEC 1986. *Environment Protection Act,* Department of Environment and Conservation, West Australia, 1986.

WHO 1999. *Guidelines for Community Noise,* Eds. Berglund, B. Lindvall, T. & Schwela, D.H. WHO task force meeting outcome, London, April 1999. Available from the WHO website http://www.who.int/en/

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